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THESIS

A PROBABILISTIC TARGET CLASSIFICATION AND DESCRIPTION MODEL FOR SEISMIC SENSORS

by

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Unattended ground sensors have a tremendous potential for providing information about battlefield targets, but for the most part this potential has been unrealized. The Marine Corps has recently fielded the Phase V seismic sensors of the Tactical Remote Sensor System (TRSS). These sensors are more sensitive than any of the previous versions, and their potential to provide more detailed target information is also greater than that of previous sensors. The current target classification and description model used by TRSS was developed for sensors which were placed in use in the early 1960's. The model is simple and deterministic in nature, and does not take into account the variance in the sensor system or the variance in sensor performance due to target type, target velocity, soil composition, or other potential factors. This thesis examines the sensor system variance and the effect of target type on sensor performance through field testing and develops an improved model for target description that accounts for these effects. The revised model takes advantage of the measured sensor characteristics to better describe the target, and provides the user with bounds that describe the credibility of the model's estimate.

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A PROBABILISTIC TARGET CLASSIFICATION AND DESCRIPTION MODEL FOR SEISMIC SENSORS

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ABSTRACT

Unattended ground sensors have a tremendous potential for providing information about battlefield targets, but for the most part this potential has been unrealized. The Marine Corps has recently fielded the Phase V seismic sensors of the Tactical Remote Sensor System (TRSS). These sensors are more sensitive than any of the previous versions, and their potential to provide more detailed target information is also greater than that of previous sensors. The current target classification and description model used by TRSS was developed for sensors which were placed in use in the early 1960's. The model is simple and deterministic in nature, and does not take into account the variance in the sensor system or the variance in sensor performance due to target type, target velocity, soil composition, or other potential factors. This thesis examines the sensor system variance and the effect of target type on sensor performance through field testing and develops an improved model for target description that accounts for these effects. The revised model takes advantage of the measured sensor characteristics to better describe the target, and provides the user with bounds that describe the credibility of the model's estimate.

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EXECUTIVE SUMMARY

Unattended ground sensors have a tremendous potential for providing information about battlefield targets, but for the most part this potential has been unrealized. The Marine Corps has recently fielded the Phase V sensors of the Tactical Remote Sensor System (TRSS), a new family of unattended ground sensors which includes seismic, infrared and magnetic sensors. The target classification and description model used by TRSS, called the Sensor Formula, was developed for use in the late 1960's. The model assumes fixed sensor detection distances based only on the target's classification type. It does not take into account the variance in sensor's detection distance due to natural variation, target type, target velocity, soil composition, or other potential factors. It arbitrarily determines target class, based on the target's velocity; that is, a target moving at less than 9 kph is classified as personnel, while a target moving at 9 kph or greater is classified as vehicle. The target description process after classification is also impeded by the deterministic nature of the solution, and the model consistently underestimates the number of individual targets within a target column. The problems discovered with the target classification and description process of the Phase V sensors have negated the potential utility of the information. The effects of these problems extend to the rest of the Marine Corps combat intelligence gathering capability.

The issue of sensor capability is critical to the classification and description problem. The available test reports concerning the TRSS seismic sensor, known as the Seismic Intrusion Device (SID), detection capabilities do not address the potential variance in target detection ranges. In order to determine the required parameters for the detection distance variable, a field experiment was conducted at Marine Corps Base, Camp Pendleton, California, using the resources of the 1st Sensor Control and Management Platoon. The experiment was conducted to determine the effects of target type and sensor sensitivity, for fixed soil composition and target velocity. Trials were done using targets representative of the Tracked vehicle, Wheeled vehicle, and Personnel target classes. The results of these tests confirm that both target type and sensor sensitivity affect SID performance. Furthermore, the expected detection distance and the corresponding variation were determined for each combination of factors.

A final factor which affects sensor performance with respect to the Sensor Formula is the existence of variable time delays built into TRSS itself. Known delays include a 2 second delay in the SID, as it self-confirms the detection, up to an additional 12 second delay, as the Encoder

Transmitter Unit (ETU) waits to send the activation message from the SID to the Sensor Monitoring System (SMS), and a possible delay of 3.75 seconds within the SMS as the message is processed. These delays have an effect on realized sensor performance which is proportional to the velocity of the target. At the upper bound of the delay, a target moving at 20 kph will have moved almost 100 meters after the SID actually detected it before the SMS reports its existence. In effect, the SID's detection range has been reduced by 100 meters. While the experiment does not specifically address this factor, knowledge of its effect is critical to understanding the sensor problem.

Having determined the appropriate sensor parameters, the next step was to revise the existing estimators for velocity, column length, and the number of elements within a column, to take advantage of the parameters. The formulae currently used by TRSS as estimators rely on data collected from two seismic sensors. As currently applied, the formulae do not adequately estimate the true target states, because the fixed values used in the formula are actually random variables whose values depend on the sensor's detection capabilities. All estimates are based on detection times, and the revised model expresses the observed times as functions of the sensor parameters. The estimators are nonlinear functions of these parameters, and the propagation of errors method is used to estimate their mean and variance. All of the current estimators were found to be positively biased, with a common bias factor. The revised estimators remove this bias, and also provide a means for assessing the variance of the estimate. This knowledge of the variance is then used to establish confidence intervals for the estimated values, based on an application of Chebyshev's inequality.

A critical portion of the problem was target classification, because selection of the appropriate sensor parameters depends on correct classification. Every target within a target class generates its own distinct seismic signature, and TRSS sensors are sensitive enough to detect the differences. The U.S. Army Remote Battlefield Area Surveillance System (REMBASS) uses similar sensors, and a target classifier which compares the target's seismic signature to an internal library of known signatures. It attempts to classify the target more precisely through repeated sampling and Bayesian updating, and attempts to classify the target as Tracked, Wheeled, or Personnel. Currently TRSS classifies targets only as Vehicle or Personnel, based on a simple comparison of the estimated velocity to a single constant value. The revised model applies the

discrete form of Bayes' Rule to determine the probability that target detected is of a specified target class, given the velocity, as reported by the sensor, the *a priori* distribution of target classes provided by the user, and an empirical *a priori* distribution of velocities for each target class.

There appear to be no existing descriptions of this last distribution, so for the purposes of this study, a survey of experienced users was conducted to determine the characteristics of the distribution. Students at the Naval Postgraduate School, who had operational experience in planning and conducting tactical movements, were questioned as to the likelihood of a column, composed of a particular target class, moving at specified velocity intervals, over different movement conditions. The results of the survey form the basis for the Bayesian classification rule.

The results of this study are clear. The objective was to determine if the current sensor algorithm could be improved, and to suggest enhancements that would provide better information to the operational commander. It has been found that the Sensor Formula can, indeed, be improved, especially in light of the sophistication of TRSS Phase V. The most significant improvements were achieved by determining the correct sensor parameters. Furthermore, now confidence intervals can be established for each estimate, which provide the user with a measure of how good the estimate is. It is recommended that the Marine Corps conduct further research into this area, especially into the effects of other soil and velocity treatments on SID detection capabilities. When these effects are more completely understood, and when the current estimators are replaced with the unbiased estimators presented here, TRSS will once again become an important, and trusted, tool in the Intelligence analysts toolbox.

I. INTRODUCTION

Unattended ground sensors have a tremendous potential for providing information about battlefield targets, but for the most part this potential has been unrealized. The Marine Corps has recently fielded the Phase V sensors of the Tactical Remote Sensor System (TRSS), a new family of unattended ground sensors which includes seismic, infrared and magnetic sensors. A detailed description of TRSS can be found in Appendix A. The purpose of TRSS is to provide Marine Air/Ground Task Force (MAGTF) commanders with intelligence information about the movements of enemy forces along routes within their Area of Interest. The Phase V sensors are more sensitive than any of the previous versions, and their potential to provide more detailed target information is also greater than that of previous sensors. Fully half of the Phase V sensors included in TRSS are seismic, and most of the target classification information provided by TRSS is taken from the seismic sensors. Approximately 75% of all sensors currently in operational use are seismic.

The target classification and description model used by TRSS, called the Sensor Formula, was developed for use in the late 1960's. The model is capable of determining two general target classes, dismounted infantry and vehicles. After classification, the target is further described based on its speed, the duration of the sensor observation, and the detection distance of the sensors. The Sensor Formula provides a target description that includes target speed, target classification, direction of movement, estimated length of the target's formation and estimated number of individual targets within the formation.

A. PROBLEM IDENTIFICATION

To date, the target classification model used by TRSS has been simple and deterministic in nature. The model assumes fixed sensor detection distances based only on the target's classification type. It does not take into account the variance in sensor's detection distance due to natural variation, target type, target velocity, soil composition, or other potential factors. It arbitrarily determines target class, based on the target's velocity; that is, a target moving at less than 9 kph is classified as personnel, while a target moving at 9 kph or greater is classified as vehicle. The target description process after classification is also impeded by the deterministic nature of the solution, and the model consistently underestimates the number of individual targets within a target column.

The Marine Corps Tactical Systems Support Activity (MCTSSA) first became aware of the potential magnitude of this problem while it was preparing the new data interpretation software package for the TRSS Phase V Sensor Monitor System (SMS). During testing, the software routinely generated results which were physically impossible, such as target formations with negative column lengths. After checking the coding process to ensure that the existing target classification and description algorithm had been implemented properly, MCTSSA realized that the problem was the result of either variance in the detection capabilities of the new Phase V sensors, or was inherent in the algorithm itself.

B. OPERATIONAL SIGNIFICANCE

The problems discovered with the target classification and description process of the Phase V sensors have negated the potential utility of the information. Although TRSS Phase V sensors continue to be used by operating forces, users have little confidence in the results, and tend to discount them. In some cases users have decided to revert to Phase III hardware and software. This is unacceptable, as the Phase III items are being phased out in favor of the newer Phase V items. Eventually the entire inventory will be replaced. If a solution cannot be found, the Phase V sensors will not be used.

The effects of this problem extend to the rest of the Marine Corps combat intelligence gathering capability. If ground sensors are removed from the MAGTF intelligence analyst's toolbox, he will be forced to get his information from other sources, such as ground reconnaissance, aerial imagery or signal intelligence units. These units are already being tasked to their maximum capacity. It may well turn out that if the MAGTF cannot collect the combat information from the sensors, it just will not be collected, and the MAGTF commander will be making his decisions based on a picture of the battlefield which is not as clear as it could be.

C. ISSUES

1. Sensor Capabilities

The issue of sensor capability is critical to the classification and description problem. The available test reports concerning the TRSS seismic sensor, known as the Seismic Intrusion Device (SID), detection capabilities do not address the potential variance in target detection ranges. The

last known report of this type, completed in July, 1993, states only that the geophones used by the SIDs have an average detection range, and that the range is based on the type of target being detected. It makes no judgments as to the variances of the ranges it reports [Ref. 1]. Empirical observations from the field, however, suggest that there is a great deal of deviation from the claimed detection ranges.

There are a number of factors which contribute to the variations in detection distance. Some of these are directly related to the location in which the sensor is emplaced, while others are due to target effects. Previous work has shown that a sensor's detection range is affected by the composition and moisture content of the soil in which the sensor is buried, as well as the depth at which the sensor is placed. Target characteristics that effect variation include target weight, velocity, and target class. [Refs. 1 and 2]

A side effect of soil composition on detection distance is that the detection area of a seismic sensor is not necessarily circular. If the soil composition is uniform between the target and the sensor, then the seismic signature of the target will attenuate smoothly as it approaches the sensor. However, the boundaries between different soil types, or bands of rock within a soil type will cause the seismic wave to refract, seriously reducing the detection range of the sensor and creating an irregularly shaped detection area. This study assumes that the sensor is placed in an area containing a homogenous soil type, and, thereby, the detection area of the sensor is circular, with the sensor placed in the center of the area.

One factor readily controlled by the user is the sensor's sensitivity setting. The TRSS SIDs have three sensitivity settings; High, Medium, and Low. The Medium setting attenuates the detection range by approximately 15%, while the Low setting reduces detection range by about 40%. Past experiments have demonstrated that the sensitivity level associated with the High setting is unacceptable, and for the purposes of this research only the Medium and Low settings will be considered. [Ref. 1, p. A4]

A final factor which affects sensor performance with respect to the Sensor Formula is the existence of variable time delays built into TRSS itself. Known delays include a 2 second delay in the SID, as it self-confirms the detection, up to an additional 12 second delay, as the Encoder Transmitter Unit (ETU) waits to send the activation message from the SID to the SMS, and a possible delay of 3.75 seconds within the SMS as the message is processed. These delays have an

effect on realized sensor performance which is proportional to the velocity of the target. At the upper bound of the delay, a target moving at 20 kph will have moved almost 100 meters after the SID actually detected it before the SMS reports its existence. In effect, the SID's detection range has been reduced by 100 meters.

2. Target Classification and Description

Every target within a target class generates its own distinct seismic signature. TRSS Phase V SIDs are sensitive enough to detect the differences, but TRSS does not take advantage of this capability. The U.S. Army Remote Battlefield Area Surveillance System (REMBASS) uses similar sensors, and has a target classifier which compares the target's seismic signature to an internal library of known signatures. It attempts to classify the target as Tracked, Wheeled, or Personnel, through repeated sampling and Bayesian updating [Ref. 3]. But, REMBASS was considered too large and heavy for amphibious operations and Marine Corps purposes. The TRSS SMS, which is lighter and more portable, does not distinguish between seismic signatures. However, since sensor detection parameters, and the Sensor Formula, are dependent on the type of target detected, classification is necessary. Future plans for TRSS call for the use of a thermal imaging sensor to resolve the classification problem, but this sensor is still in its developmental stages. The general process which TRSS follows to classify and describe a target has six stages, and is illustrated in Figure 1. Currently TRSS classifies targets as Vehicle or Personnel, based on a simple comparison of the estimated velocity to a single constant value.

The formula currently used by TRSS to determine the length of a target column relies on data collected from two seismic sensors. As currently applied, this formula does not adequately estimate the true length of column, because the fixed values used in the formula are actually random variables whose values depend on the sensor's detection capabilities. Similarly, the formula used by TRSS to determine the number of targets within a target column is inaccurate because it treats the reported column length as a fixed value, instead of a function of random variables. Reports from the field indicate that the current sensor algorithm consistently underestimates both the length of observed columns and the number of targets within the column.

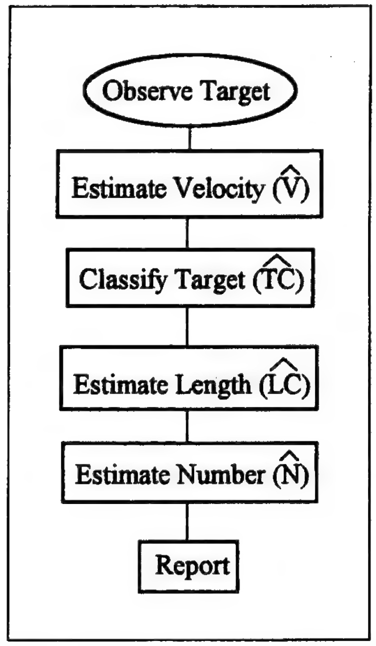


Figure 1. Target Classification and Description Process.

3. Human Interfaces

Human interface with the target classification problem occurs in both sensor emplacement and in the analysis of the sensor activations to be used by the Sensor Formula. In general, human interface problems will not be considered by this study. It is assumed that operators will emplace the sensors properly, and that they will properly interpret the sensor activations reported. However, as a general reference, brief mention will be made of the most significant human interface issues.

Improper placement of the sensors can greatly effect their detection capabilities. The sensor's detection capability will be reduced, or the sensor may not report at all, if the geophone is incorrectly oriented. If the sensor's sensitivity setting is not properly made, or if it is recorded incorrectly, the data transmitted by the sensor will be incorrectly analyzed by the Sensor Formula. Once the sensors have been emplaced and report a target, the SMS console operator is responsible for selecting the activations which the Sensor Formula will use to classify the target. The activations are displayed as symbols on the SMS console display. The selection is made by placing a cursor near the activation symbol. The software interface which presently executes the Sensor Formula reads the time corresponding to the cursor location, not the time associated with the

nearest activation symbol. If the operator places the cursor too far from the symbol, the Sensor Formula will use inaccurate values for the times, and the resulting estimates for column length and number of targets will also be inaccurate.

D. PROBLEM STATEMENT

To develop a Sensor Formula that will provide a more accurate target description, and takes into account the variation due to system time delays, sensor sensitivity, target type and target velocity. The revised Sensor Formula should take advantage of known sensor characteristics to better describe the target, and to provide the user with bounds that describe the credibility of the model's estimate.

II. BACKGROUND

A. HISTORY

1. Early Development

Development of an unattended ground sensor system began in September, 1966, at the direction of Secretary of Defense Robert McNamara. The intended mission of the system was to monitor the movement of enemy forces in Southeast Asia. By November, 1967, the first operational evaluation was being performed, as the sensor system was used to provide target acquisition for Air Force strike aircraft. Early in the following year, the sensors were first used in direct support of ground forces, when they were used to provide early warning and target acquisition for artillery during the defense of the combat base at Khe Sanh. These successes encouraged the Department of Defense to increase the operational employment of the sensors, and by mid-1968, they enjoyed widespread use throughout Southeast Asia. At this point, the sensors employed were in Phase I of their development. Phase I technology consisted of seismic sensors and transmitters which were limited to line of sight communications.

In 1971, sensor employment was formalized in the Marine Corps, as the first three Sensor Control and Management Platoons (SCAMP) were established. By this time in their development, the sensor system technology had reached Phase II, which included more accurate sensors, more powerful transmitters, and a limited relay capability. Phase II sensors were first introduced to Southeast Asia in 1970. By mid-1971, the first Phase III sensors began to be employed, initially as a classified program. [Ref. 4]

2. Phase III and Later Development

The Phase III program dramatically increased the capabilities of the sensor suite. The program included hand emplaced seismic, acoustic, magnetic and infrared sensors, air delivered seismic sensors, more channels, powerful relays and an increased resistance to electronic warfare operations. The Battlefield Area Surveillance System (BASS III) was also introduced. BASS was a highly mobile monitoring system which greatly enhanced the ability to monitor sensors. The

system was generally mounted in a shelter which fit on the bed of a 5-ton truck, but also included a monitoring system which could be mounted inside a UH-1 helicopter.

Phase III provided a reliable system which had widespread use throughout the Marine Corps and U.S. Army for the next twenty years. Development continued, however, with the objective of providing a system with worldwide capabilities, since Phase III sensors had been engineered specifically for employment in Southeast Asia. This effort became Phase IV of the sensor program, and ended with the fielding of the Remotely Monitored Battlefield Area Sensor System (REMBASS) by the U.S. Army in 1984. The Marine Corps did not accept REMBASS, citing weight, expense, lack of an air deliverable sensor, and inability to support amphibious operations as the primary reasons for its rejection. The Marine Corps then started its own development efforts for the sensor suite, which has become Phase V of the overall effort, and has yielded TRSS. [Ref. 4]

B. TRSS

1. Enhancements

The TRSS Phase V sensor suite consists of a family of remotely monitored, unattended ground sensors, and the support equipment which transmits, displays and analyzes the sensor data. As with the previous sensor phases, detection is accomplished primarily with a Seismic Intrusion Detector (SID), but the suite also includes an Infrared Intrusion Detector (IRID), a Magnetic Intrusion Detector (MAGID) and an Air Delivered Seismic Intrusion Detector (ADSID). A digital thermal imaging sensor is currently under development. Phase V sensors are currently being fielded in the Fleet Marine Forces, and the current operational mix consists of approximately 30% Phase III equipment and 70% Phase V equipment.

The Phase V effort provides a major upgrade to the 20 year old Phase III sensors. The suite uses improved technology to provide sensors which are lighter, have a longer transmission range, are more resistant to electronic warfare measures, and run on standard household batteries. It also provides the ability to record data that can be stored and evaluated at a later date. Emplacement, operating and monitoring techniques are similar to those used for the Phase III system. A complete description of TRSS Phase V is given in Appendix A.

2. Employment

TRSS sensors are employed to provide continuous all-weather detection, location and monitoring of activity within a given area. The primary mission of the SCAMPs, which employ the sensors, is Battlefield surveillance. The specific missions most commonly performed are Route Surveillance and Target Indication. As the sensors are used to monitor choke points, roads and trails, they are expected to provide descriptive information which can be correlated with other intelligence information.

The sensors are generally emplaced in groups containing a mixture of seismic and other sensors. The seismic sensors are used to provide the highest proportion of the target information, primarily because of their abundance and reliability. At least two SIDs will be placed in each sensor string. Other sensors, especially the IRID, are used in conjunction with the SID to confirm its reporting. The confirming sensors are also capable of providing more detailed information than the SID. For example, both the IRID and the MAGID are capable of counting targets as they pass the sensor, and the MAGID can also help to classify targets based on their metal content. [Refs. 4 through 6]

C. FACTORS AFFECTING DETECTION CAPABILITY

1. Location Factors

The effects of soil composition, topography and surface composition on seismic attenuation are well documented, and are the primary source of confounding variables, or "noise", in the target detection problem [Refs. 2 and 3]. However, their effects have not been well quantified, nor applied to refine detection probabilities. It is extremely difficult for the sensor operator to determine the characteristics of the sensor emplacement site with enough precision to allow him to better predict the sensor's detection capability. In recognition of this, operators are instructed to test the actual detection capabilities of each sensor they emplace by using a portable monitoring device and walking through the detection area to determine its limits. Unfortunately, tactical requirements often preclude such a test, and in any event, the test would not provide the operator with information regarding the sensor's ability to detect vehicles.

2. Target Factors

The characteristics of the target have a significant impact on the SID's detection capability. Any force emanating from the target and coming in contact with the ground will create a seismic signature. Both aircraft and helicopters, for example, flying over a seismic sensor will be detected because the soundwave produced by their engines and rotors strikes the ground and creates a distinctive seismic signature. The seismic signature of the target depends on the target's weight, velocity and mode of movement. Targets such as tracked vehicles and rapidly moving dismounted personnel, which strike the ground as they move, produce relatively clear and strong seismic signature, while wheeled vehicles and more slowly moving personnel produce weaker signals. Engine and other mechanical noise is also transmitted as seismic activity and increases the signature of vehicles. [Refs. 4 and 6]

D. TARGET CLASSIFICATION ALGORITHMS

1. The Sensor Formula

The current sensor formula is nearly 30 years old, and has been used continuously with Phase I through Phase III sensors, and continues to be used with TRSS. The formula relies on four observations from a pair of adjacent sensors (see Figure 2). Each sensor reports the time when it first detects the target, and the time when it last detects the target. These times are shown as T_i in the figure. The parameters used by the formula to classify and describe the target are

d	the straight line distance between the sensors,
Tm	the Time that the target took to travel from one sensor to the next,
$TT1$	the Total Time the target was detected by the first sensor,
CDR	the Combined average Detection Radius of the two sensors,
V	the target's average velocity,
$\hat{V}$	the velocity estimator,
LC	the target's average column length,
$\hat{LC}$	the length estimator,
N	the number of elements in the column, and
$\hat{N}$	the estimator for the number of elements in the column.

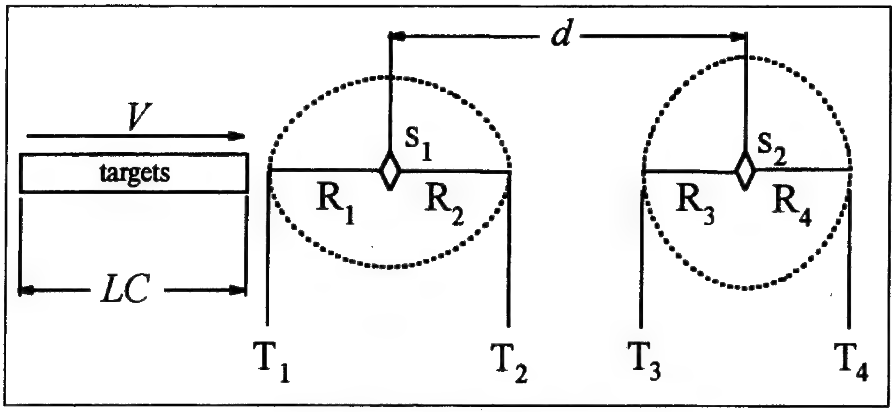


Figure 2. Sensor Geometry.

The formula estimates average velocity through simple time/distance calculations involving the known distance between two sensors, and the time it takes the target to travel between them. Activations from either seismic or infrared sensors can be used to determine velocity. For the seismic sensors, the formula used to estimate velocity is

$$\hat{V} = \frac{d}{Tm}. \tag{1}$$

Once target velocity has been calculated, the total distance traveled by the target as it passes through one sensor's detection area is determined by multiplying the velocity by the total time the target is detected by that sensor. Only seismic sensors can be used to provide this time, as they are the only type of sensor which are capable of continuously detecting the target. Finally, the length of the target column is estimated by subtracting the sum of the average detection distances of the two sensors. The formula used to estimate LC is

$$\begin{aligned} L\hat{C} &= \left(\frac{d}{Tm}\right) TT1 - CDR \\ &= (\hat{V} \cdot TT1) - CDR. \end{aligned} \tag{2}$$

Note that in the current formula, $CDR = \mathrm{E}[R_1] + \mathrm{E}[R_3]$, even though R_1 and R_2 are used to estimate LC. To be correct, CDR should be the expected value of the detection <u>diameter</u>. In its

present form, *CDR* is accurate only if the two sensors have the same sensitivity setting. Once the length of the target column has been estimated, the total number individual targets within the column is also estimated. The formula used by TRSS to estimate the number of targets within a target column is

$$\hat{N} = \frac{L\hat{C}}{Int} \tag{3}$$

where *Int* is the expected interval between individual vehicles (usually 50 meters) or personnel (usually 5 meters) within the target column, and is specified by the user each time the Sensor Formula is used. The value of $\hat{N}$ is always rounded up to the next highest integer value. Note that this formula will always incorrectly estimate the number of items in the column, even given perfect information about the column length and interval between items, because it fails to account for the extra item which must be included in order to create the intervals (that is, $N + 1$ items are required to create N intervals), and because it does not consider the length of the items themselves.

2. Alternatives

TRSS uses a very simple method to classify targets--if the target velocity is less than 9 kph, the target is classified as Personnel. If the velocity is greater than or equal to 9 kph, the target is classified as Vehicle. A more sophisticated method of target classification is that employed by REMBASS, which compares the signature it receives from a target to an internal library of seismic signatures. The REMBASS classifier is capable of producing Personnel, Wheeled vehicle and Tracked vehicle (PWT) classifications. However, as previously stated, REMBASS is not an acceptable alternative for the Marine Corps.

The REMBASS PWT classifier relies on a Bayes minimum error decision rule, based on target observations. The target's seismic signature is repeatedly sampled and compared to the decision rule, until an assurance threshold is reached and the target is classified. The classifier compares the target observations with progressively more difficult rules in its library, that is, it first attempts to classify the target as personnel, then a wheeled vehicle, etc. If no classification can be made, the classifier simply returns the result "Detected". Otherwise, it returns the most likely target classification. [Ref. 3]

An additional enhancement of REMBASS, presently under study, is a site adaptive classifier improvement which allows the user to measure and take into account the effects of the sensors location on seismic signature attenuation. The user input serves as a baseline which the REMBASS classifier uses to improve the target classification data received from the sensor. As each detection message is received, the enhanced classifier will use the target observations to classify not only the target, but also to classify the site in which the sensor is located. A library of standard site classifications will be maintained in the processor, and site characteristics will be used to modify data received from a sensor in a particular site. Initial research has shown that the site adaptive classifier can improve automatic classification performance by an average of 1.9%, and operated assisted classification performance by 11.3%. [Ref. 3]

III. METHODOLOGY

A. SENSOR WEAKNESSES

1. Baseline Detection Capability

As previously mentioned, estimates of the SID's mean detection distance for various target classes have been made, but there is no evidence of existing estimates for variance in the distances. In the current Sensor Formula, the detection distances are treated as constants, but they are more accurately classified as random variables. The expected value and variance of the Phase V SID detection distance were unknown. The first requirement, then, was to conduct an experiment and collect data which could be used to characterize the detection distance random variable. The data from the experiment was also used to test the existing estimates for mean detection distance.

The baseline estimates for detection distance used to setup the experiment were those stated in the TRSS Operator's Course [Ref. 6]. These distances are detailed in Table 1, and were apparently derived from an experiment done by the Structures Laboratory of the U.S. Army Corps of Engineers Waterways Experiment Station in 1993 [Ref. 1]. The experiment was conducted both to verify these distances and to allow for detections different from those reported.

TRSS SID Detection Distances (meters)					
Surface Type	**Target Class**				
	Sensitivity	Dismounted Troops	Light Wheeled	Heavy Wheeled	Tracked
Paved Surface	Medium	45	50	200	300
	Low	15	20	50	300
Gravel Surface	Medium	NA	100	300	300
	Low	NA	50	150	300
Cross Country	Medium	85	150	300	300
	Low	20	100	300	300

Table 1. Baseline detection distances [from Ref. 6].

2. Detection Distance Experiment

In order to determine the required parameters for the detection distance variable, a field experiment was conducted at Marine Corps Base, Camp Pendleton, California, using the resources of the 1st SCAMP. The experiment was conducted so that the factors of target type, velocity, soil composition and sensor sensitivity were held constant for each trial. Due to cost and time constraints, only one soil composition was tested, and the test site was selected to achieve maximum possible uniformity of soil composition. The soil type in the test area was classified, according to the Defense Mapping Agency scale, as ML7, Inorganic silts and very fine sands. The United States Department of Agriculture, Soil Conservation Service, rating of this soil was a mixture of HrC, Huerhuero loam, and EdC, Fine Sandy loam. The test area sloped slightly down towards the sensors, so that seismic attenuation could be minimized. An open field was used as the test track, with targets following a specific course across the field. Since the test track corresponds to the cross country classification used by the previous reports, the targets should produce the most distinct seismic signatures and the longest detection distances. See Figure 3.

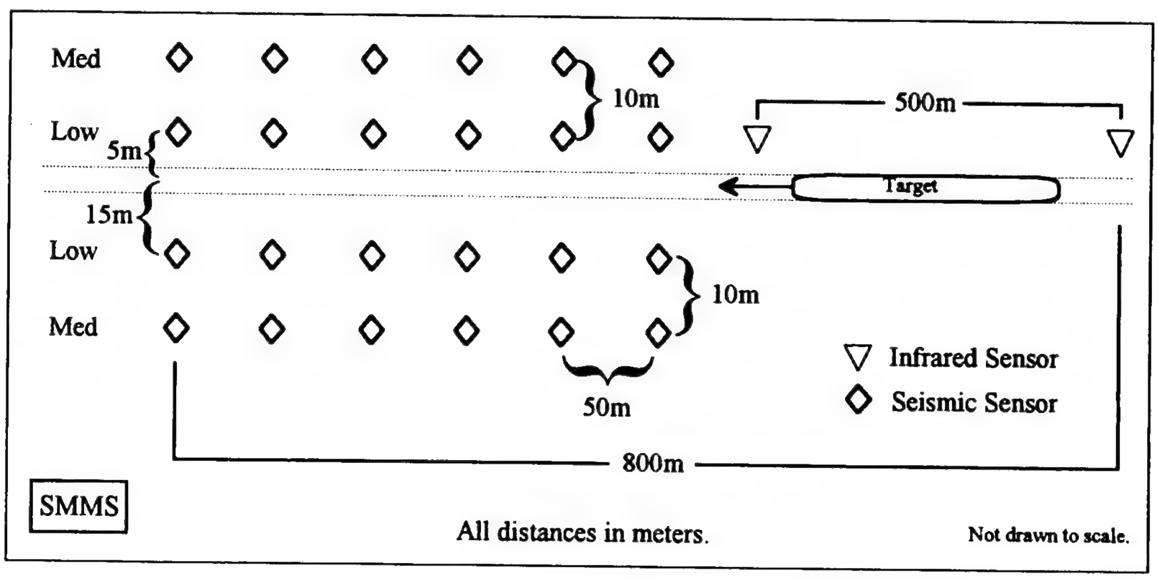


Figure 3. Seismic Sensor Experiment Layout.

A field of 24 sensors was emplaced, consisting of a 12 SIDs set for low and 12 set for medium sensitivity. The track and sensors were oriented so that the targets approached the sensors from at least 500 meters away and then traversed the entire sensor field, so that as many sensors as

possible would be activated by each target run. The Sensor Mobile Monitor System (SMMS) was established far enough away from the sensor field so that the vibrations of its generator did not activate the sensors, but close enough so that the operators could observe the target runs.

Targets representing all target classes were used. An LVTP-7 Amphibious Assault Vehicle (AAV) was used to represent the Tracked classification. An M923 5-ton truck and an M1098 High Mobility Multi-Wheeled Vehicle (HMMWV) were used for the Heavy and Light Wheeled categories. The Personnel classification was represented by 12, 24, and 36 man units. All vehicles conducted the experiment without any cargo, and the personnel units did not have weapons and were equipped only with their load bearing equipment.

As each target traveled down the test track, the time it started the run and the time it reached a point 50 meters from the sensor field were noted by infrared sensors and an observer traveling in the target, and reported to the SMS. The time the target passed each sensor row was also recorded by the observer. The readings from the infrared sensors and the times recorded by the observer were used to determine the target's actual velocity for each run. The Tracked target runs were done at a velocity of 20 kph, the Wheeled runs at 15 kph, and the Personnel runs at approximately 5 kph. The targets stopped moving as soon as they had cleared the last sensor.

3. Detection Distance Random Variable

Experimental results were used to characterize the distribution of the random variable associated with detection distance, R, which, given soil type, depends on the sensor sensitivity setting and target type. The empirical distributions were analyzed and compared to families of known distributions to determine which most accurately models R. The mean detection distance and variance for each combination was estimated from the experimental data. Where possible, the mean of R was tested against those suggested by the Operator's Course. The detection distance, r_{ij}, for each sensor i recorded by the SMS during each trial j, was calculated using the time the sensor activated (t_{j1}), the time the target was adjacent to the sensor (t_{j0}), the target's velocity (v_j), and the distance from the sensor to the test track (h_i; see Figure 2) by the formula

$$r_{ij} = \sqrt{(h_i)^2 + (v_j[t_{j0} - t_{j1}])^2} \tag{4}$$

B. SENSOR ALGORITHMS

As previously stated, the problem is to first classify a target as a member of a general class, and then to describe the target, given that it is a member of that class. The result provided to the user will be a list of potential target descriptions and the confidence level associated with each description.

1. Assumptions

It is expected that the sensors will be employed as defined by current Marine Corps' doctrine. Because of that, this study assumes that the distance between sensors is known accurately and that the targets are moving parallel to a line drawn through the sensors' locations. The later assumption follows from the fact that the sensors are generally placed adjacent to a trail or road, in order to provide surveillance of traffic moving on the route. [Refs. 4 through 6]

It also follows from employment doctrine that the targets can be assumed to be moving at an average velocity, *V*, and have an average length, *LC*, which do not vary, through the sensors' detection area. Sensors are generally placed well away from intersections or other likely areas which might cause a target to change its velocity. The sensors are also placed close enough together so that the target's column length will not change significantly during detection. Throughout this study all targets are assumed to maintain a constant velocity and length.

A final assumption is that the detection area of a sensor is generally circular. This means that the detection distance of a sensor is equal for both targets that are approaching the sensor's position and targets departing the sensor's position. The result of this is that R_1 and R_2, in Figure 4, are independently and identically distributed, as are R_3 and R_4, although possibly with a different distribution.

2. Velocity Estimate

As stated above, the current model estimates velocity from the sensor observations by the Equation 1, which simply calculates velocity as the quotient of *d*, the known distance between two sensors, and *Tm*, the time it took a point in the target to travel between those sensors (See Figure 4). *Tm* is presently stated as a function of the detection times observed by the sensor, that is, as

$$Tm = \left[T_3 + \left(\frac{T_4 - T_3}{2}\right)\right] - \left[T_1 + \left(\frac{T_2 - T_1}{2}\right)\right]. \tag{5}$$

However, Tm can also be expressed as a function of the appropriate realizations of R as

$$Tm = \frac{R_1 - R_2 - R_3 + R_4 + 2d}{2V}, \tag{6}$$

so the distribution of $\hat{V}$ is a function of the distribution of R. See Appendix B for details of how the T's and the R's are related. Note that $\hat{V}$ it is not a linear function of R, so its mean and variance will not simply be linear functions of E[R] and Var(R). Once the distribution of R is known, then the distributions of Tm and $\hat{V}$, and their expectations, can also be determined.

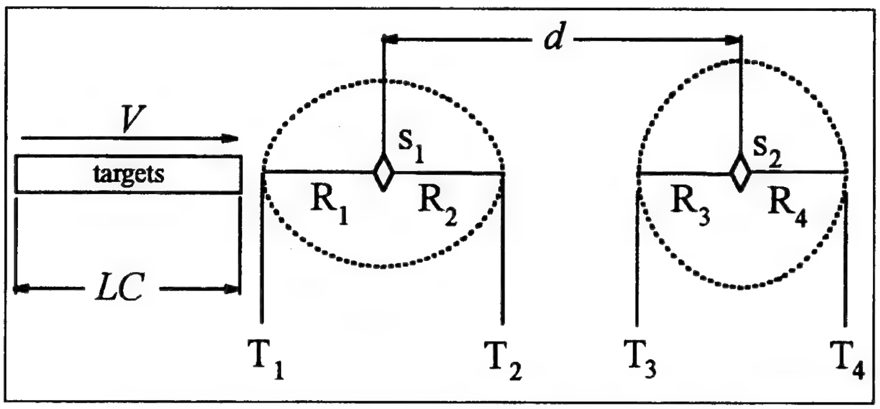


Figure 4. Sensor Observations as Basis for Estimates.

3. Target Classification

In the current model, all targets whose reported velocity is less than 9 kph are classified as dismounted infantry, while all targets whose velocity is greater than or equal to 9 kph are classified as vehicles. The revised model will apply the discrete form of Bayes' Rule to determine the probability that target detected is of a specified target class TC_i, given the velocity, V, reported by the sensor, the *a priori* distribution of target classes TC provided by the user, and an empirical *a priori* distribution of velocities for each target class. That is,

$$Pr(TC_i|\hat{V}) = \frac{Pr(TC_i)Pr(\hat{V}|TC_i)}{\sum_j Pr(TC_j)Pr(\hat{V}|TC_j)}, \tag{7}$$

where $Pr(\hat{V}|TC)$ is the multinomial distribution describing velocity (see Appendix C.). The result will be a list of target classifications and the probability that the target of interest belongs to each specific class. After classification, a target description will be provided for each potential target classification.

4. Target Description

The current deterministic TRSS target description model will be used as a basis for the probabilistic model. The model relies on the fact that column length is merely a function of the number of items in the column and the interval between those items. It first estimates the column length based on the target's velocity and classification, and then works backwards to estimate the number of vehicles or personnel in the column.

a. Length of Column

The target's column length is equal to total distance traveled by the column, while being detected by one of the sensors, minus the combined detection distances of sensors. Distance traveled is determined by multiplying the target's velocity and the length of time the target was reported moving at that velocity. However, since the total distance traveled as reported by the sensor includes the detection distance of the sensor which provided the reports, it must be removed.

The current model is

$$L\hat{C} = (\frac{d}{Tm} \cdot TT1) - CDR. \tag{8}$$

One source of errors in the current model is the use of bad *CDR* values (actually, for the $E[R_i]$). This formula can also be expressed as

$$L\hat{C} = d\,(\frac{TT1}{Tm}) - CDR. \tag{9}$$

*TT*1 is generally expressed, as a function of observed time, as

$$TT1 = T_2 - T_1. \tag{10}$$

It can also be expressed as a function of R, of the true column length, LC, and of the velocity, V. This expression is

$$TT1 = \frac{R_1 + R_2 + LC}{V}. \tag{11}$$

Note that Equation 10 uses R_1 and R_2, so CDR should be (E[R_1] + E[R_2]), and not (E[R_1] + E[R_3]). Therefore, $\hat{LC}$ can be written, as a function of the observations of R, given the true column length LC, as

$$\hat{LC} = 2d\left(\frac{R_1 + R_2 + LC}{R_1 - R_2 - R_3 + R_4 + 2d}\right) - (E[R_1] + E[R_2]). \tag{12}$$

The revised model will attempt to reduce the variance of $\hat{LC}$ by including the observation of both sensors to yield TT, the total time the target was observed by both sensors. TT is

$$TT = \frac{(T_2 - T_1) + (T_4 - T_3)}{2}$$

$$= \frac{R_1 + R_2 + R_3 + R_4 + 2LC}{2V}. \tag{13}$$

Now let E[R_1] = E[R_2] = μ_1, since R_1 and R_2 are identically distributed, and let E[R_3] = E[R_4] = μ_2, for the same reason. Then the revised formula for the estimated column length becomes

$$\hat{LC} = d\left(\frac{R_1 + R_2 + R_3 + R_4 + 2LC}{R_1 - R_2 - R_3 + R_4 + 2d}\right) - \left(\frac{2\mu_1 + 2\mu_2}{2}\right). \tag{14}$$

If sensor 1 and sensor 2 are both set on the same sensitivity level, this reduces to

$$\hat{LC} = d\left(\frac{R_1 + R_2 + R_3 + R_4 + 2LC}{R_1 - R_2 - R_3 + R_4 + 2d}\right) - 2\mu_1. \tag{15}$$

The estimate of column length is then a random variable that is a function of the known distance d, the sensor detection distance R, whose distribution has been determined empirically, and the true column length LC. Note that the target's velocity, V, does not directly affect $\hat{LC}$. The distribution of $\hat{LC}$ can now be determined as a function of the distribution of R (see Chapter IV).

b. Number of Targets

The current target description model estimates the number of individual items in the target column by dividing the column length by an estimate of the interval between targets, and rounding up. The interval estimate is provided by the user, and is doctrinally 50 meters for vehicles and 5 meters for personnel.

The revised model will account for variation in the interval between individuals in the column, and will express the number of targets as a random variable, $\hat{N}$. Its distribution will be a function of the estimated column length, $\hat{LC}$, and the expected value of the variable, *Int*, which describes the sum of a column element's mean individual length and the mean interval length between it and the succeeding element, which will vary by target class. It is important to include the element's length in the value of *Int*, especially when the ratio of element length to interval between elements is relatively large. Failing to do so will result in estimates which consistently overestimate the actual number of elements. Both $\hat{LC}$ and *Int* are dependent on the target classification made by the algorithm. The value of E[*Int*] for a specific target class can be determined by expert opinion and empirical observation. The revised model for the distribution of the number of targets in the column will be

$$\hat{N} = \frac{\hat{LC}}{E[Int]} + 1\,, \tag{16}$$

for each possible target class TC. The final value of $\hat{N}$ for each set of sensor observations will be expressed as a confidence interval about E[$\hat{N}$] (see Chapter IV).

5. Confidence Intervals for the Estimates

Once the values of $\hat{V}, L\hat{C}$, and $\hat{N}$ have been determined, the final step in the target description process is to express confidence intervals for each estimate, based on the distributions formed as functions of the distribution of R. For the distributions that can not be determined, or are intractable, Chebyshev's inequality is used to place conservative bounds on the estimates (see Chapter IV).

IV. RESULTS

A. SENSOR PARAMETERS

1. Limitations of the Experiment

Several obstacles arose during the conduct of the experiment which hindered the data collection effort. First, the training area in which the experiment was conducted was adjacent to one in which CH-53E helicopters and AV-8B Harrier VSTOL jets were conducting training, and several runs had to be discarded because of the seismic interference caused by the aircraft. Fortunately, the seismic signature of an aircraft is readily discernible on the SMS screen.

A more serious concern was the fact that the IRIDs used to record the start times for the target runs began to malfunction intermittently during the Personnel test and the Light Vehicle test. At irregular intervals, either or both would begin to activate continuously. Both the IRIDs and their respective ETUs were replaced, but the replacements also began to malfunction. As a result, the base time used in determining the detection distance for each sensor, t_{0j} in Equation 4, could not be precisely observed. In some cases, the proper time could be determined from the time and position records of the observer traveling with the target. In those cases where it could not, the data was discarded.

An unexpected difficulty appeared during the post-collection data analysis. It was initially desired to find a single family of distributions which could be used to generally approximate the distribution of the detection distance, R, for each target classification. However, none could be found which provided an acceptable model for estimation. Not only did it appear that the distributions were different between target types, but the distributions also varied between sensitivity settings.

Since no common family of distributions could be found which would provide a general method to approximate the distribution of R, the propagation of error method was used to approximate Tm and TT as functions of R. This method expresses $\hat{V}$ and $L\hat{C}$ as functions of R using Taylor series expansions. A second order expansion is used to approximate the mean of each distribution, and a first order series is used to estimate the variance.

A final obstacle, also noted during data analysis, was that the sensors were not placed optimally on the test track. In some cases, most notably among the sensors set on the low sensitivity setting during the Personnel test, some sensors did not activate during some test runs, presumably because they were placed too far away from the track. Future experiments should ensure that all sensors are placed within 2 meters of the track, to ensure more activations.

In addition, it would have been better to extend the test track several hundred meters beyond the sensor field, in order to collect data on the "departing" detection distance of the sensors. As it was, some data was collected on this distance (R_2 and R_4 in Figure 4), but not enough to make any conclusions about its relationship to the "arriving" detection distance (R_1 and R_3).

2. Results of the Experiment

The results of the experiment are tabulated below, with a separate table for each target type. Each table list the value of *TC* tested, as well as the parameters observed. The parameters reported are

n	number of observations in the sample,
μ_L	mean detection distance, on the low setting,
s_L	sample standard deviation of the detection distance, on the low setting,
μ_M	mean detection distance, on the medium setting, and
s_M	sample standard deviation of the detection distance, on the medium.

a. *Personnel Targets*

As noted above, the results of the experiment for the Personnel target class were the most affected by the problem with the IRIDs. However, the low velocity of the target, combined with the maximum possible timing errors, yields calculated detection distances that will still be within 4.5 meters of the true distance for any given observation. Assuming that the timing error is uniformly distributed between -3 and 3 seconds, the expected error is zero, and overall will have no effect on the mean distances, but will effect variance. The results of the experiment are given in Table 2, and in Figures 5 and 6.

	Parameter									
Target	n	Min_L	Max_L	μ_L	s_L	n	Min_M	Max_M	μ_M	s_M
12 Pers	64	5.00	63.95	15.60	14.58	93	15.00	49.75	22.07	7.20
24 Pers	78	5.00	101.12	19.04	17.80	105	15.00	104.59	27.49	15.77
36 Pers	19	5.00	92.40	23.53	23.85	32	15.00	88.88	25.70	15.63
Combined	161	5.00	101.12	18.02	17.51	230	15.00	104.59	25.05	13.16

Table 2. Results of Experiment with Personnel Targets.

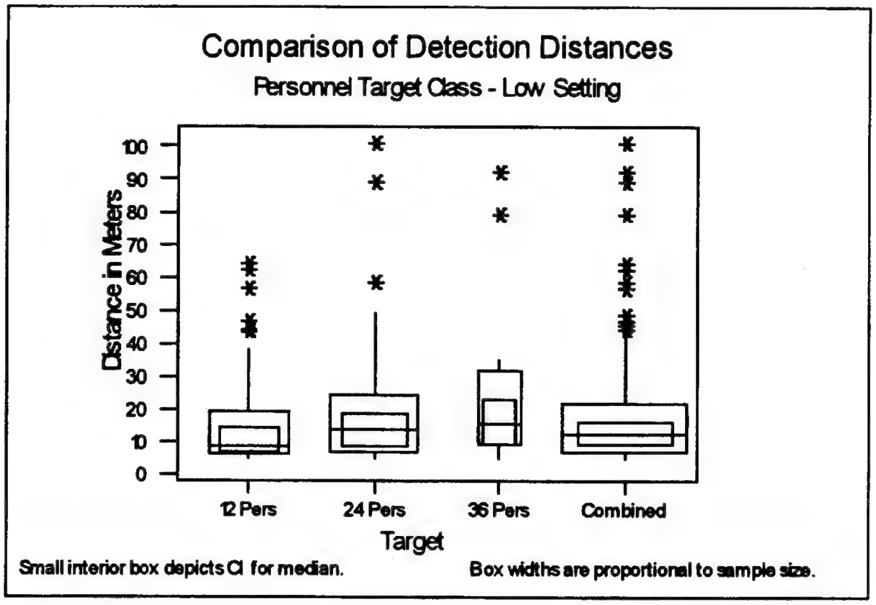


Figure 5. Comparison of Personnel Detection Distances - Low Setting.

Figures 5 and 6 show that the distribution of detection distance, for each of the three target sizes, is similar. Nonparametric tests were applied to verify this observation. The hypotheses H_0: $(R|12\ Pers) = (R|24\ Pers) = (R|36\ Pers)$, that there was no difference in detection distance between target sizes, was tested for each sensitivity setting, using the Kruskal-Wallace test with $\alpha = 0.05$. For the low sensitivity setting, the test failed to reject H_0, with a significance level of 0.157 (adjusted for ties). For the medium sensitivity setting, the test also failed to reject H_0, with a significance level of 0.094 (adjusted for ties). Since the hypothesis that the distribution of $(R|Pers)$ is independent of the number of personnel in the column could not be rejected, the data sets were combined, and the statistics for the Combined sets are also shown in Table 2. The

parameters used for the remaining calculations will be those for the Combined distribution of ($R|Pers$). Finally, the Mann-Whitney test was used to test H_0: ($R_{LOW}|Pers$) = ($R_{MED}|Pers$), that there was no difference between sensitivity settings. The test rejected H_0, with an observed significance level of less than 0.001. See Figure 7.

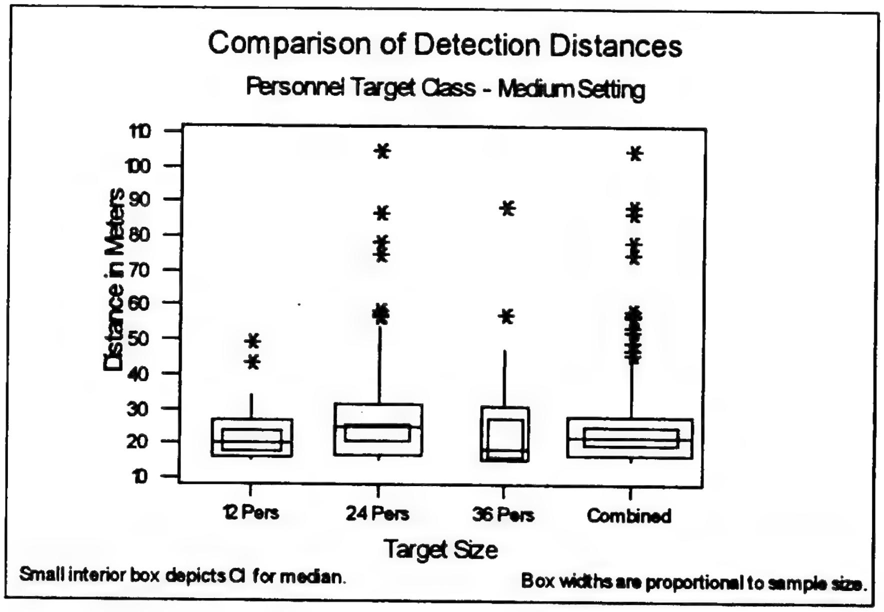


Figure 6. Comparison of Personnel Detection Distances - Medium Setting.

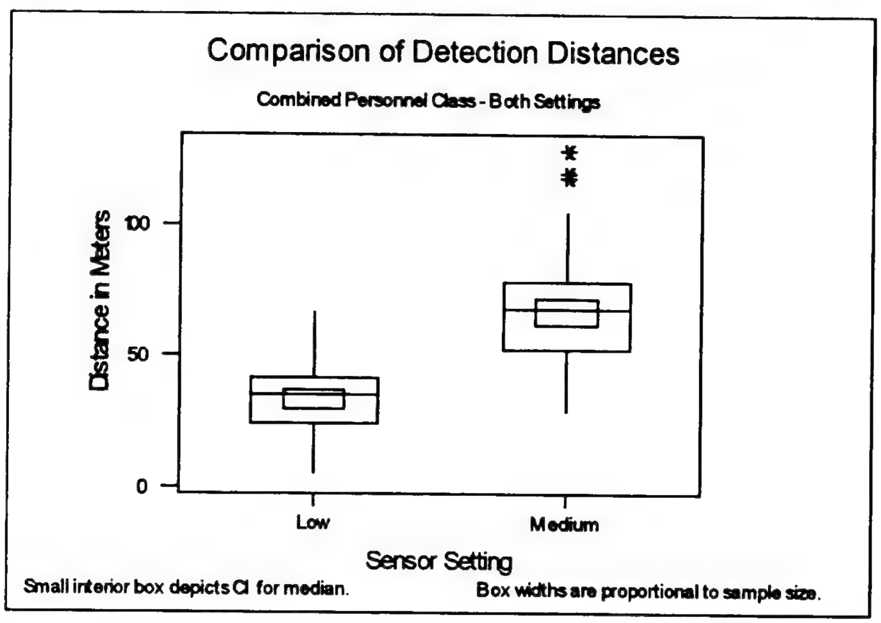


Figure 7. Comparison of Combined Personnel Detection Distances - Both Settings.

b. Wheeled Vehicle Targets

Separate experiments were done to determine the parameters of the detection distance variable using the Heavy Wheeled Vehicle and Light Wheeled Vehicle classifications. The results of the test are given in Table 3 and Figure 8.

	Parameter									
Target	**n**	**Min_L**	**Max_L**	**μ_L**	**s_L**	**n**	**Min_M**	**Max_M**	**μ_M**	**s_M**
Lt Wheeled	68	5.00	55.40	28.48	11.53	64	28.79	89.72	56.76	15.82
Hvy Wheeled	60	8.67	66.01	38.99	11.99	60	40.50	128.03	75.90	18.56

Table 3. Results of Experiment with Wheeled Targets.

Figure 8 also shows that the detection distributions are different, both for target class and for sensitivity setting. The data were also tested against each other to determine if the came from the same distribution. Four pairwise comparisons, with the pairs Lt-Low/Hvy-Low, Lt-Low/Lt-Med, Hvy-Low/Hvy-Med, and Lt-Med/Hvy-Med were made, using the Mann-Whitney test. All tests rejected the hypotheses, with observed significance levels of less than 0.001.

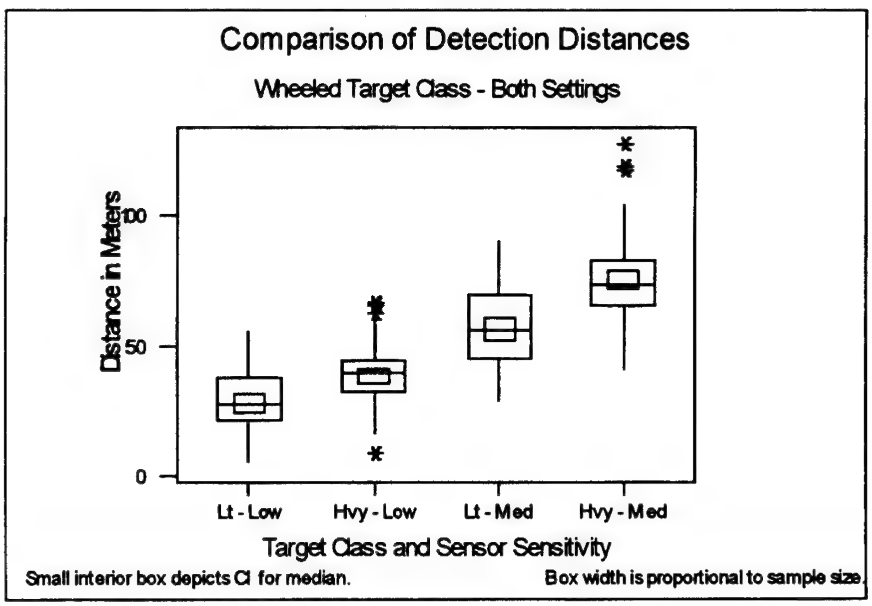


Figure 8. Comparison of Wheeled Target Detection Distances - Both Settings.

Knowledge of the differences in detection capabilities against Light and Heavy Wheeled Vehicles is directly useful, however, only if the Sensor Formula is able to discern the difference between these two types of targets. Since the classification algorithm will only classify targets as Wheeled, and since is unlikely that any column observed will consist exclusively of either Light or Heavy Wheeled Vehicles, a mixture of the two detection capabilities is required. In fact, since, for tactical reasons, it is possibly more likely that any column of wheeled vehicles will both begin and end with a light vehicle, an argument could be made that all targets classified as Wheeled should use the Light Wheeled parameters. This model will assume that either is equally likely, and will estimate the detection parameters by using a uniform mixture of the two samples, for each sensitivity setting. There is some danger in this if, for example, the resulting distribution is bimodal, but Figures 9 and 10 show this is not so. The results of the mixtures are given in Table 4 and Figure 11.

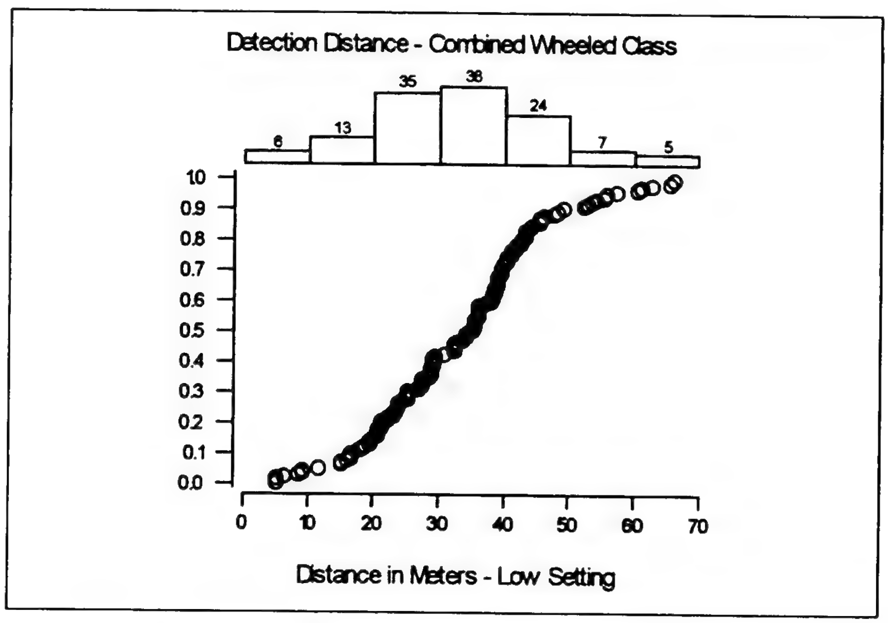


Figure 9. Combined Wheeled Detection Distances - Low Setting.

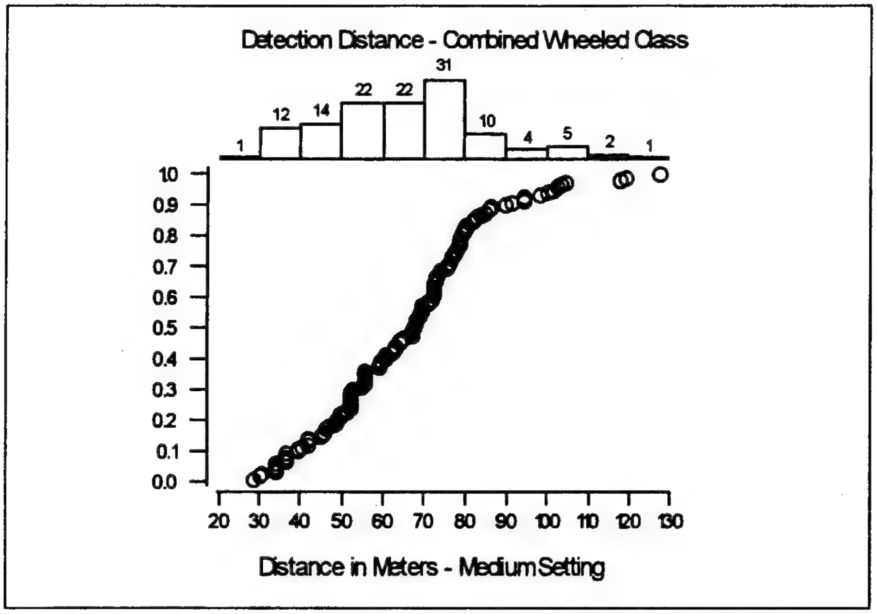


Figure 10. Combined Wheeled Detection Distances - Medium Setting.

	Parameter									
Target	n	Min_L	Max_L	μ_L	s_L	n	Min_M	Max_M	μ_M	s_M
Wheeled	128	5.00	66.01	33.40	12.83	124	28.78	128.02	66.02	19.64

Table 4. Results of Combining Wheeled Vehicle Classes.

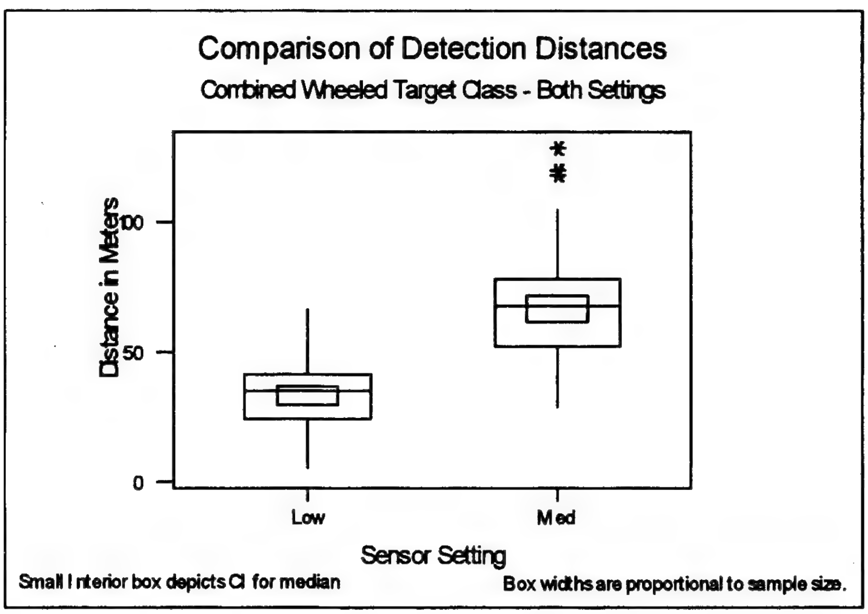


Figure 11. Comparison of Combined Wheeled Target Detection Distances - Both Settings.

As with previous samples, the Mann-Whitney test was used to verify that the different sensitivity settings produced different distribution for R. In this case, the test rejected the null hypothesis, with a significance level of less than 0.001.

c. *Tracked Vehicle Targets*

Two types of trials were run with the AAV. The first, which made up the majority of the trials, consisted of the AAV driving through the sensor field at a velocity of 20 kph. In the second type, which made up only one trial, the AAV moved through the sensors at a velocity of approximately 39 kph. Although the trial at this higher velocity only provided 24 data points, it appears that target velocity may have little effect on a sensor's detection distance. The results of these experiments are summarized in Table 5, and in Figures 12 and 13.

	Parameter									
Target	**n**	**Min_L**	**Max_L**	**μ_L**	**s_L**	**n**	**Min_M**	**Max_M**	**μ_M**	**s_M**
Tracked	148	64.62	207.25	119.83	26.03	144	54.55	261.04	174.35	34.32
Fast Tracked	12	67.44	165.07	119.33	31.62	12	112.40	209.71	169.40	34.55
Combined	160	64.62	207.25	119.79	26.33	156	54.55	261.04	173.97	34.19

Table 5. Results of Experiment with Tracked Targets.

It is seems obvious from Figures 12 and 13 that velocity has little effect on the distribution of R. To verify this, the data sets for each target velocity and each sensitivity setting were then tested by the Mann-Whitney test to determine if they could have been drawn from the same distribution. The tests failed to reject the hypotheses that the distributions of R for the Slow and Fast velocities were the same, with observed significance levels of 0.982 and 0.673, for the Low and Medium sensitivity settings, respectively. The test did reject the hypothesis that the Low and Medium settings produced the same results, with an observed significance level of less than 0.001. See Figure 14.

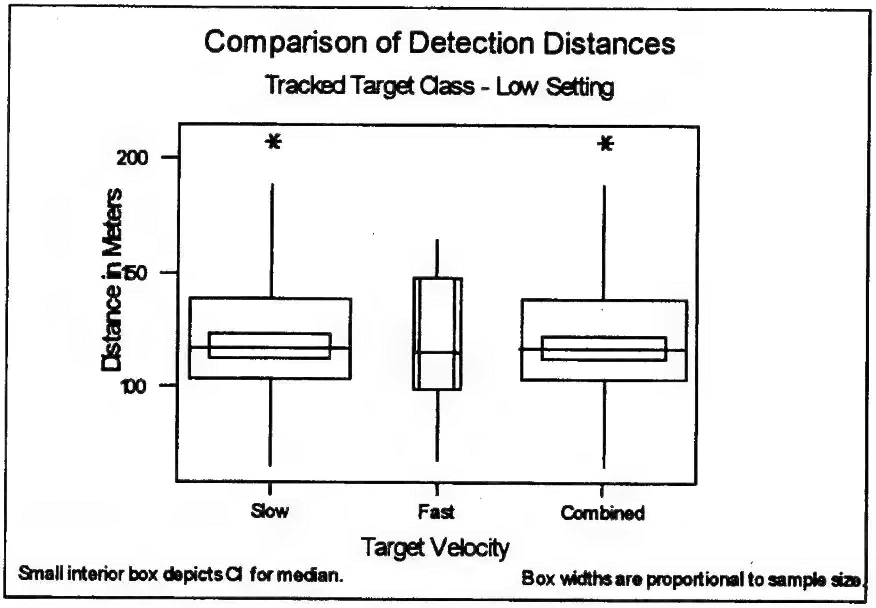


Figure 12. Comparison of Tracked Target Detection Distances - Low Settings.

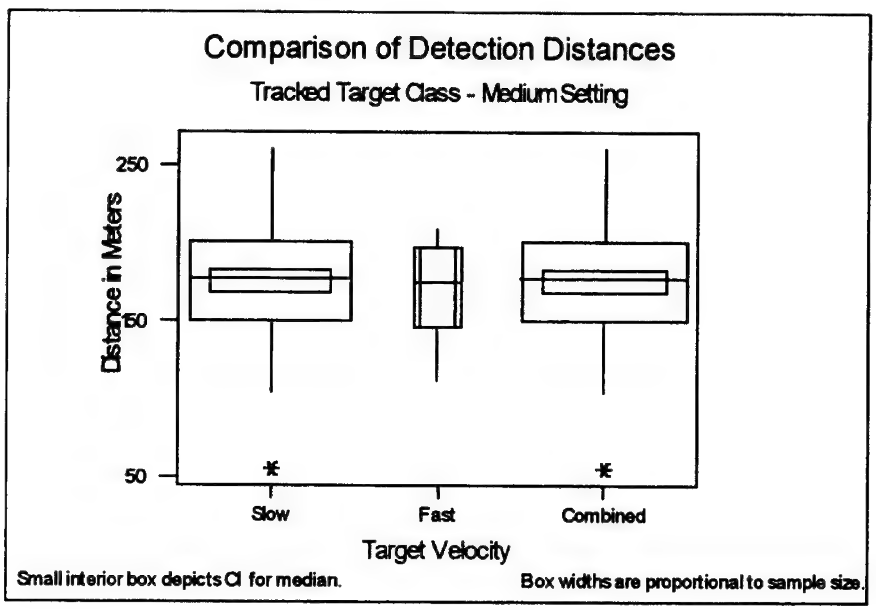


Figure 13. Comparison of Tracked Target Detection Distances - Medium Settings.

d. *Comparison with Previous Results*

The results of the experiment were compared to those published in the TRSS operator's manual. The differences are illustrated in Figures 15 and 16. Both figures clearly

demonstrate the problem with the detection distances published in the Operator's Course. They do not represent the performance actually experienced by operators in the field. Since the Sensor Formula relies so heavily on these parameters, its accuracy will depend directly on that of the estimates of the sensors' detection distances.

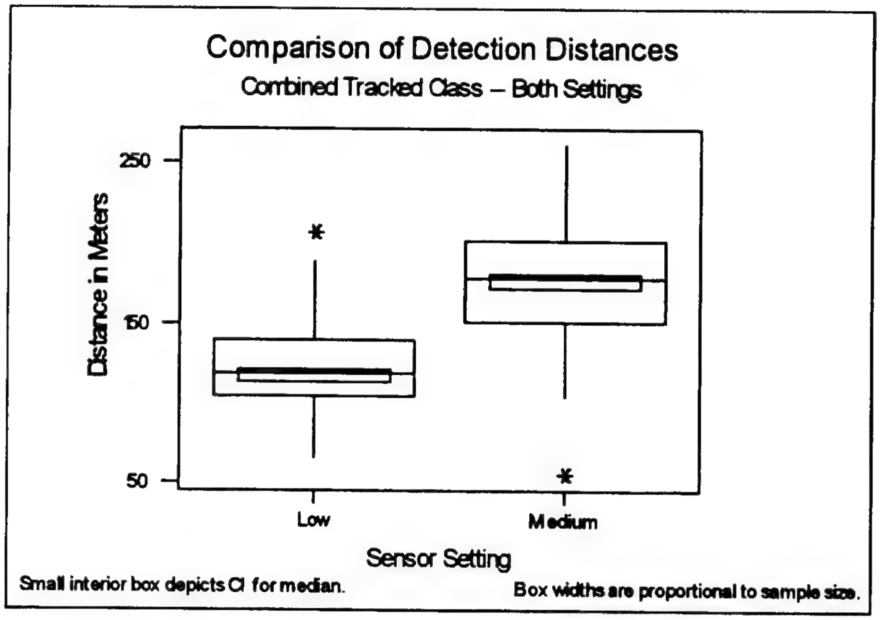


Figure 14. Comparison of Tracked Detection Distances - Both Settings.

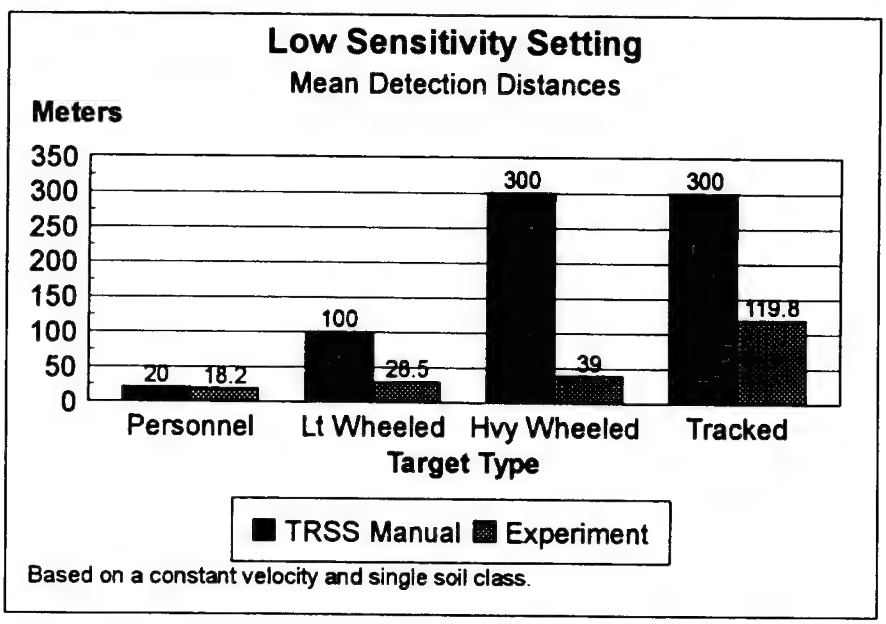


Figure 15. Comparative Results - Low Sensitivity Setting.

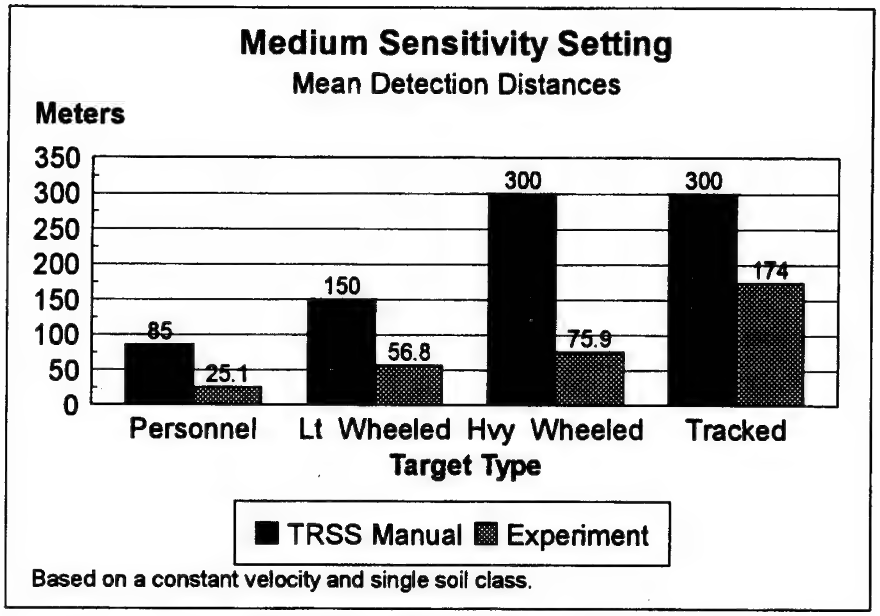


Figure 16. Comparative Results - Medium Sensitivity Setting.

The Wilcoxon Signed Rank test was used to compare the median values of the experiment trials with the average detection distances stated in the manual. The observations made from the Figures above were verified by the results of these tests. The data from each of the target-sensitivity settings was tested against the median for that combination listed in the Operator's Manual. All eight tests conducted rejected the hypothesis that the sample medians were the same as the published detection distances, at a significance level of less than 0.001.

B. SENSOR FORMULA

1. Velocity Estimate

The current method of estimating target velocity has produced generally satisfactory results, but analysis shows that it is positively biased. Removing this bias, and recognition of the variance of the estimate, will improve the performance of both the target classification and description models.

a. *Expected Value*

The second order Taylor series expansion of $\hat{V}$ about μ_{Tm} is

$$\hat{V} \approx \frac{d}{\mu_{Tm}} - \left(\frac{d}{\mu_{Tm}^2}\right)(Tm - \mu_{Tm}) + \frac{1}{2}\left(\frac{2d}{\mu_{Tm}^3}\right)(Tm - \mu_{Tm})^2. \tag{17}$$

From the above, since $E[(Tm - \mu_{Tm})] = 0$, the expected value of $\hat{V}$ is

$$E[\hat{V}] \approx \frac{d}{\mu_{Tm}} + \frac{d}{\mu_{Tm}^3}\sigma_{Tm}^2$$

$$= \frac{d}{\left(\frac{d}{V}\right)} + \frac{1}{\left(\frac{d}{V}\right)^3}\left(\frac{\sigma_1^2 + \sigma_2^2}{2V^2}\right)$$

$$= V(1 + \frac{\sigma_1^2 + \sigma_2^2}{2d^2}). \tag{18}$$

Equation 18 clearly shows that this method of estimating V is positively biased. The magnitude of the bias can be controlled through the selection of the sensor sensitivity setting, which determines the values of σ^2_i, and by increasing the distance between the sensors. Combining the sensor-dependent parameters to form σ_c^2, the unbiased estimator of V, named $\hat{V}'$, is formed by

$$\hat{V}' = \left(\frac{d}{Tm}\right)(1 + \sigma_c^2)^{-1}. \tag{19}$$

This estimator is not yet useful, however, because the parameter σ^2_c depends on the target class observed, and the target is not classified until after $\hat{V}'$ has been calculated. It will

be shown below that target classification can still be accomplished using the biased estimator of V, and that once the target has been classified, the bias can be removed to report the unbiased velocity estimate.

b. Variance

The first order Taylor series expansion of $\hat{V}$ about μ_{Tm} is given by

$$\hat{V} \approx \frac{d}{\mu_{Tm}} - \frac{d}{\mu_{Tm}^2}(Tm - \mu_{Tm}), \tag{20}$$

and, using the bias correction factor derived in Equations 18 and 19, the variance of the revised $\hat{V}'$ is

$$\begin{aligned} Var(\hat{V}') &\approx (1+\sigma_c^2)^{-2}\sigma_{Tm}^2\left(\frac{d^2}{\mu_{Tm}^4}\right) \\ &= (1+\sigma_c^2)^{-2}\left(\frac{\sigma_1^2+\sigma_2^2}{2V^2}\right)\left(\frac{d^2}{\left(\frac{d}{V}\right)^4}\right) \\ &= V^2\,\sigma_c^2\,(1+\sigma_c^2)^{-2}. \end{aligned} \tag{21}$$

Note that since the bias correction factor is greater than one, the variance of the revised estimator is less than that of the original method. Unfortunately, the variance of $\hat{V}'$ depends on the true value of V. However, Equation 21 also shows that for any given values of V and target class, the variance of its estimate is inversely proportional to the square of the distance between the sensors used. The magnitude of var($\hat{V}'$) can be predetermined, and to a great extent limited by, the positioning of the sensors on the ground. The farther apart they are placed, the smaller the variance of the estimate is likely to be.

c. Confidence Interval

Since the distribution of R is not known, for any given values of V and target class, Chebyshev's inequality can be used to place bounds on the goodness of the velocity estimate by

$$Pr(|\hat{V}' - \mu_{\hat{V}'}| \leq t) \geq 1 - \frac{\sigma^2_{\hat{V}'}}{t^2} \approx 1 - \alpha. \tag{22}$$

This form allows a confidence interval of size $2t$ to be found for the desired probability. Equation 22 can be used to find a (1-α)100% confidence interval for V, given $\hat{V}'$, through the following manipulation:

$$Pr(|\hat{V}' - \mu_{\hat{V}'}| \leq t) \geq 1 - \frac{\sigma^2_{\hat{V}'}}{t^2} \approx 1 - \alpha$$

$$\Rightarrow Pr(|\hat{V}' - V| \leq t) \geq 1 - \frac{\sigma^2_{\hat{V}'}}{t^2} \approx 1 - \alpha. \tag{23}$$

since $\mu_{\hat{V}'} = v$. Therefore, for the inequalities to hold,

$$t = \frac{\sigma_{\hat{V}'}}{\sqrt{\alpha}}$$

$$\Rightarrow Pr\left(|\hat{V}' - V| \leq \frac{\sigma_{\hat{V}'}}{\sqrt{\alpha}}\right) \geq 1 - \alpha. \tag{24}$$

From this, and using Equation 21, lower and upper bounds of the confidence limit for V can be found. The upper bound is

$$V - \hat{V}' \leq \frac{V\sigma_c(1 + \sigma_c^2)^{-1}}{\sqrt{\alpha}}$$

$$V - \frac{V\sigma_c(1 + \sigma_c^2)^{-1}}{\sqrt{\alpha}} \leq \hat{V}'$$

$$V < \frac{\hat{V}'}{\left(1 - \frac{\sigma_c(1+\sigma_c^2)^{-1}}{\sqrt{\alpha}}\right)}. \tag{25}$$

Similarly, the lower bound of the confidence interval is found to be

$$V > \frac{\hat{V}'}{\left(1 + \frac{\sigma_c(1+\sigma_c^2)^{-1}}{\sqrt{\alpha}}\right)}. \tag{26}$$

The confidence level for the true velocity, based on a given observation, is found by substituting the observed velocity and the sensor parameters into Equations 25 and 26. For example, given a Wheeled target, moving at an observed velocity of 7.2 kph, detected by two sensors on the medium setting, which are 300 meters apart, a 90% confidence interval for V is

$$\frac{\hat{V}'}{\left(1 + \frac{\sigma_c(1+\sigma_c^2)^{-1}}{\sqrt{\alpha}}\right)} < V < \frac{\hat{V}'}{\left(1 - \frac{\sigma_c(1+\sigma_c^2)^{-1}}{\sqrt{\alpha}}\right)}$$

$$\frac{7.2}{\left(1 + \frac{0.067}{\sqrt{0.1}}\right)} < V < \frac{7.2}{\left(1 - \frac{0.067}{\sqrt{0.1}}\right)}$$

$$(5.95 \text{ kph} < V < 9.12 \text{ kph}).$$

2. Classification

a. General

The TRSS classification problem is a common decision theory problem for which Bayes' Rule provides a solution. In general terms, there exists a population consisting of m classes, and we wish to classify an individual as belonging to a specific i of those classes, based on some observed measurement. In TRSS, the population is all targets on the battlefield, and the

problem is to classify any given target as a member of the class TC, based on the velocity as measured by the SIDs, where TC_i has the values

TC_P = Personnel (P),

TC_W = Wheeled vehicle (W), and

TC_T = Tracked vehicle (T).

Bayes' Rule calculates the posterior distribution of the target's type. The Intelligence Officer first provides the prior probability, π_i, that a target is of a given type i. These probabilities are denoted $\{\pi_P, \pi_W, \pi_T\}$. This information is readily available from his order of battle database. In the absence of such data, he can assign a uniform prior probability of 1/3 to each classification.

This method also requires the user to know the distribution of velocity, given target type. This information is not readily available, so a survey of experienced personnel was conducted to establish baseline distributions for four movement conditions. The results of this survey are tabulated in Appendix C. Given the π_i, the Intelligence Officer's prior beliefs, v, the target's velocity, and $Pr(Vel = v|TC = TC_i)$, the discrete distribution of velocity by target types, the target can be classified by

$$Pr(TC = TC_i|Vel = v) = \frac{\pi_i Pr(Vel = v|TC = TC_i)}{\sum_K \pi_k Pr(Vel = v|TC = TC_k)}. \tag{27}$$

However, the value reported by the sensors is $\hat{V}$, not V. Knowing that $E[\hat{V}] = V(1 + \sigma_c^2)$, we can transform Equation 27 to classify the target based on $\hat{v}$:

$$Pr(TC = TC_i|Vel = \hat{v}) = \frac{\pi_i Pr(Vel = (1 + \sigma_c^2)v|TC = TC_i)}{\sum_K \pi_k Pr(Vel = (1 + \sigma_c^2)v|TC = TC_k)}. \tag{28}$$

For each target class TC_i, Equation 28 will yield the probability that the observed target belongs to that class, based on the biased velocity observation. Once so classified, the

unbiased velocity estimate can be calculated and reported to the user, and the column length and number of elements of each target can be estimated using the corresponding sensor parameters.

b. Posterior Risk

If desired, Bayes' Rule can also be used to assess the posterior risk of a classification. Posterior risk is defined as the expected risk of assigning a target to a specific class. It can be determined by first establishing the loss value *l(i,j)*, that is, some measure of the importance to the user of mistakenly classifying a target of class TC_i to the class TC_j. The posterior risk of assigning a target to TC_i is PR_i, and is found by

$$PR_i = \frac{\sum_{k=1}^{m} l_{ki}\pi_k Pr(Vel = v|TC = TC_k)}{\sum_{j=1}^{m} \pi_j Pr(Vel = v|TC = TC_j)}. \qquad (29)$$

In the special case where the loss value, *l(i,j)*, corresponding to a mistaken classification is 1, then the associated total loss, *Loss(i)*, is simply the risk of incorrectly classifying the target. That is,

$$Loss(i) = PR_i = \frac{\sum_{k\neq i}(1)\pi_k Pr(Vel = v|TC = TC_k)}{\sum_{j=1}^{m} \pi_j Pr(Vel = v|TC = TC_j)}$$

$$= Pr(TC \neq TC_k|Vel = v)$$

$$= 1 - Pr(TC = TC_k|Vel = v). \qquad (30)$$

In those cases where the Intelligence Officer can assign a loss value to mistaken classification, the value acts as a weight which adjusts the posterior risk in accordance with his beliefs about the importance of the target classes. In such a case, the classification which minimizes the posterior risk is the target classification assigned to the target.

c. *Classification Example*

Suppose the MAGTF is deployed in the desert, and the G-2 has assessed the distribution of target types in a portion of his Area of Interest as follows, based on order of battle information:

$$\pi_P = 0.1,$$

$$\pi_W = 0.5,$$

$$\pi_T = 0.4.$$

The SCAMP has placed SIDs along an unimproved road in the Area of Interest. The sensors activate, and report a target velocity of 7.2 kph. Using the distribution of velocity by target type for an unimproved road (Appendix C), the Bayes' classification method will classify the target as given in Table 6.

Target	Probability
Personnel	0.20
Wheeled	0.44
Tracked	0.36

Table 6. Target Classification Example.

The current TRSS classification method will classify this target as Personnel. The Bayesian method shows that it is more likely that the target is Wheeled. Given the G-2 has assigned no specific loss value to misclassification, then the associated posterior risks are given in Table 7.

Target	Risk
Personnel	0.80
Wheeled	0.56
Tracked	0.64

Table 7. Posterior Risk Example

In this case, the target classification rule will classify the target as Wheeled, since that classification minimizes the posterior risk. However, the G-2 might still be concerned about this classification, because the risk values for Wheeled and Tracked classifications are so close. Suppose that the he can assign loss values to miscalculation. For instance, the G-2 determines that classifying either a tracked or wheeled vehicle target as a personnel target will incur a relative loss of 10, and that classifying a tracked target as wheeled will give a loss of 5. All other mistaken classification retain a value of 1. Table 8 shows that the posterior loss value associated with each classification changes significantly.

Target	Loss
Personnel	8.02
Wheeled	2.02
Tracked	0.64

Table 8. Posterior Loss Values.

In this case, classifying the target as a Tracked vehicle will minimize the loss. That is the classification the revised method will make.

3. Column Length Estimate

The principal cause for error in the current Sensor Formula estimator for column length is the use of incorrect sensor parameters. However, the formula for column length is itself biased, and removing this bias will improve the model's accuracy.

a. *Expected Value*

Let the mean detection distance of the first sensor be denoted μ_1, and let that of the second sensor be μ_2. Then the second order Taylor series expansion of $L\hat{C}$ about μ_{TM} and μ_{TT} is

$$L\hat{C} \approx \left[d\left(\frac{\mu_{TT}}{\mu_{Tm}}\right) - (\mu_1 + \mu_2)\right] - \left(\frac{d\,\mu_{TT}}{\mu_{Tm}^2}\right)(Tm - \mu_{Tm}) + \left(\frac{d}{\mu_{Tm}}\right)(TT - \mu_{TT})$$

$$+\frac{1}{2}\left(\frac{2d\,\mu_{TT}}{\mu_{Tm}^{3}}\right)(Tm-\mu_{Tm})^{2}-\left(\frac{d}{\mu_{Tm}^{2}}\right)(Tm-\mu_{Tm})(TT-\mu_{TT})\,. \tag{31}$$

The expected value of $\hat{LC}$ is found by taking the expectation of the right-hand side. Note that the covariance of Tm and TT is zero, for when expressed in terms of R_y, it is of the form cov($X+Y$, $X-Y$), which equals zero. Evaluating the expected value of the terms, we find

$$E[\hat{LC}]=\left[d\left(\frac{\mu_{TT}}{\mu_{Tm}}\right)-(\mu_1+\mu_2)\right]+\sigma_{Tm}^{2}\left(\frac{d\,\mu_{TT}}{\mu_{Tm}^{3}}\right), \tag{32}$$

which, when evaluated in terms of the true column length and the sensor parameters, is

$$E\left[\hat{LC}\right]=LC(1+\sigma_c^2)+(\mu_1+\mu_2)\,\sigma_c^2\,. \tag{33}$$

This is clearly a biased estimator of LC. Correcting $\hat{LC}$ to produce an unbiased estimator yields $\hat{LC}'$:

$$\hat{LC}'=\left[\hat{LC}-\sigma_c^2(\mu_1+\mu_2)\right](1+\sigma_c^2)^{-1}. \tag{34}$$

Expressed in terms similar to the old model, and in terms of the sensor observations and the sensor parameters, $\hat{LC}'$ becomes

$$\begin{aligned}\hat{LC}'&=\left(\frac{d}{1+\sigma_c^2}\right)\left(\frac{TT}{Tm}\right)-CDR\left(\frac{1-\sigma_c^2}{1+\sigma_c^2}\right)\\&=\hat{V}'\cdot TT-\left(\frac{1-\sigma_c^2}{1+\sigma_c^2}\right)CDR\,.\end{aligned} \tag{35}$$

Equation 35 is the revised Sensor Formula's unbiased estimator of the target column's length.

b. Variance

The first order Taylor series expansion of $\hat{LC}$ about μ_{TM} and μ_{TT} is

$$\hat{LC} \approx \left[d\left(\frac{\mu_{TT}}{\mu_{Tm}}\right) - (\mu_1 + \mu_2)\right] - (Tm - \mu_{Tm})\frac{d\,\mu_{TT}}{\mu_{Tm}^2} + (TT - \mu_{TT})\frac{d}{\mu_{Tm}}. \tag{36}$$

Taking the variance of this result term by term yields the variance of $\hat{LC}$, which is

$$Var\left[\hat{LC}\right] = \sigma_{Tm}^2\left(\frac{d^2\,\mu_{TT}^2}{\mu_{Tm}^4}\right) + \sigma_{TT}^2\left(\frac{d^2}{\mu_{Tm}^2}\right). \tag{37}$$

Stating this equation in terms of the true target length and the sensor parameters yields

$$Var(\hat{LC}) = \sigma_c^2\ (\mu_1 + \mu_2 + LC)^2. \tag{38}$$

Correcting for the bias of $\hat{LC}$, the variance of the revised unbiased estimator $\hat{LC}'$ is therefor

$$Var(\hat{LC}') = \sigma_c^2\ (1 + \sigma_c^2)^{-2}\ (\mu_1 + \mu_2 + LC)^2. \tag{39}$$

As with var($\hat{V}'$), var($\hat{LC}'$) is a function of the true value of the variable measured, as well as of the sensor parameters. Since σ_c^2 is inversely proportional to d, the variance of the estimate can be minimized, for any given value of LC, by the choice of sensor settings and the distance between sensors.

c. *Confidence Interval.*

Confidence intervals for LC' can be stated using Chebyshev's inequality, in the same manner as was done for $\hat{V}'$:

$$Pr(|\hat{LC}' - \mu_{\hat{LC}'}| \le t) \ge 1 - \frac{\sigma_{\hat{LC}'}^2}{t^2} \approx 1 - \alpha. \tag{40}$$

$$\Rightarrow Pr(|\hat{LC}' - LC| \le t) \ge 1 - \frac{\sigma_c^2(1 + \sigma_c^2)^{-2}(\mu_1 + \mu_2 + LC)^2}{t^2} \approx 1 - \alpha. \tag{41}$$

$$\Rightarrow Pr\left(|\hat{LC}' - LC| \leq \frac{\sigma_c (1+\sigma_c^2)^{-1}(\mu_1 + \mu_2 + LC)}{\sqrt{\alpha}} \right) \geq 1 - \alpha. \tag{42}$$

Finally, using the same method as was used for the confidence interval around V, the (1-α) 100% confidence interval for LC is stated as

$$Pr\left(\frac{\hat{LC}' - \left(\frac{\sigma_c (1+\sigma_c^2)^{-1}(\mu_1 + \mu_2)}{\sqrt{\alpha}} \right)}{\left(1 + \frac{\sigma_c (1+\sigma_c^2)^{-1}}{\sqrt{\alpha}} \right)} \leq LC \leq \frac{\hat{LC}' + \left(\frac{\sigma_c (1+\sigma_c^2)^{-1}(\mu_1 + \mu_2)}{\sqrt{\alpha}} \right)}{\left(1 - \frac{\sigma_c (1+\sigma_c^2)^{-1}}{\sqrt{\alpha}} \right)} \right) = 1 - \alpha. \tag{43}$$

The confidence level for the true column length, based on a given observation, is found by substituting the observed column length and the sensor parameters into Equation 43. Continuing with the previous example, given a Wheeled target, detected by two sensors on the medium setting, which are 300 meters apart, if the observed column length is 240 meters, an approximate 90% confidence interval for LC is

$$\left(\frac{240 - \left(\frac{0.067(65+65)}{\sqrt{0.1}} \right)}{\left(1 + \frac{0.067}{\sqrt{0.1}} \right)} \leq LC \leq \frac{240 + \left(\frac{0.067(65+65)}{\sqrt{0.1}} \right)}{\left(1 - \frac{0.067}{\sqrt{0.1}} \right)} \right)$$

(175.70 meters $\leq LC \leq$ 338.56 meters).

4. Number of Elements Estimate

The estimate of the number of individual elements in a column, $\hat{N}$, is a linear function of the estimate of the target's column length. The modifications for this estimator are a combination of the direct result of those made to $\hat{LC}$, recognition of the fact that $N+1$ objects in a column are required to form N intervals, and the fact that individual element length influences total column length.

a. *Expected Value*

Let Veh_i be a random variable which represents the length of a vehicle i in the target column. Let Int_i be a random variable which represents the interval between the ith and the $i+1$st vehicle in the column. Then the length of a column containing N vehicles is

$$LC = \left[\sum_{i=1}^{N-1} (Veh_i + Int_i)\right] + Veh_N$$

$$= [(N-1)(\mu_{Veh} + \mu_{Int})] + \mu_{Int}. \tag{44}$$

The expected values of *Veh* and *Int* can be determined from order of battle information. Let $\mu_{TInt} = (\mu_{Veh} + \mu_{Int})$. From this, another expression for N is

$$N = \frac{LC + \mu_{Int}}{\mu_{TInt}}. \tag{45}$$

Since $E[LC] = \mu_{LC} = E[\hat{LC}']$, we can substitute $\hat{LC}'$ into Equation 45 to form an unbiased estimator for N which is based on the sensors. This estimator is

$$\hat{N}' = \frac{\hat{LC}' + \mu_{Int}}{\mu_{TInt}}. \tag{46}$$

which should be rounded up to provide a conservative integer estimate. When the ratio of μ_{Int} and μ_{TInt} approaches one, this equation provides an estimator that is similar to the current model's. The differences are $\hat{LC}'$, the unbiased estimate for LC, and the addition of one, to account for the vehicle forming the last interval. However, in most cases this ratio will not be sufficiently close to one. For example, the ratio for personnel moving in a common staggered double column would be approximately $\frac{2}{3}$, while the ratio for a column of standard U.S. 5- ton trucks moving according to current doctrine is approximately $\frac{50}{58}$. In either case, failure to use μ_{TInt} instead of just μ_{Int} will lead to estimates which are consistently higher than the true value of N.

b. Variance

The variance of $\hat{N}'$ is a linear function of the variance of $\hat{LC}'$, because only the expected values of *Veh* and *Int* are used to form the estimator. Therefor, the variance of $\hat{N}'$ is

$$Var(\hat{N}') = \left(\frac{\sigma_c^2 (1+\sigma_c^2)^{-2} (\mu_1 + \mu_2 + LC)^2}{\mu_{TInt}^2} \right), \tag{47}$$

which, as for $\hat{V}'$ and $\hat{LC}'$, can be minimized by the choice of *d* and the sensors settings used.

c. Confidence Interval

Chebyshev's inequality again serves as the tool for placing bounds on the estimate. As with the $\hat{LC}'$, the variance of $\hat{N}'$ is based on the actual column length, *lc*, which itself is a linear function of *n*. Using Equation 47 for var($\hat{N}'$), Chebyshev's inequality states

$$Pr(|\hat{N}' - \mu_{\hat{N}'}| \le t) \ge 1 - \frac{\sigma_{\hat{N}'}^2}{t^2} \approx 1 - \alpha. \tag{48}$$

$$\Rightarrow Pr(|\hat{N}' - N| \le t) \ge 1 - \frac{\sigma_{\hat{N}'}^2}{t^2} \approx 1 - \alpha. \tag{49}$$

$$\Rightarrow Pr\left(\left|\hat{N}' - N\right| \le \frac{\sigma_c (1+\sigma_c^2)^{-1} (\mu_1 + \mu_2 + LC)}{\mu_{TInt} \sqrt{\alpha}} \right) \ge 1 - \alpha. \tag{50}$$

The lower bound of the confidence interval is

$$\hat{N}' - N \le \frac{\sigma_c \, (\mu_1 + \mu_2 + LC)}{(1+\sigma_c^2)\, \mu_{TInt} \sqrt{\alpha}}$$

$$\hat{N}' - N \le \frac{\sigma_c \, (\mu_1 + \mu_2)}{(1+\sigma_c^2)\, \mu_{TInt} \sqrt{\alpha}} + \frac{\sigma_c \, LC}{(1+\sigma_c^2)\, \mu_{TInt} \sqrt{\alpha}}$$

$$\hat{N}' - \frac{\sigma_c \, (\mu_1 + \mu_2)}{(1+\sigma_c^2)\, \mu_{TInt} \sqrt{\alpha}} \le N + \frac{\sigma_c \, LC}{(1+\sigma_c^2)\, \mu_{TInt} \sqrt{\alpha}}.$$

Now, inverting Equation 45 to find LC in terms of N,

$$\hat{N}' - \frac{\sigma_c\,(\mu_1+\mu_2)}{(1+\sigma_c^2)\,\mu_{TInt}\,\sqrt{\alpha}} \leq N + \mu_{TInt}\left(N - \frac{\mu_{Int}}{\mu_{TInt}}\right)\left(\frac{\sigma_c}{(1+\sigma_c^2)\,\mu_{TInt}\,\sqrt{\alpha}}\right)$$

$$\hat{N}' - \frac{\sigma_c\,(1+\sigma_c^2)^{-1}(\mu_1+\mu_2)}{\mu_{TInt}\,\sqrt{\alpha}} \leq N + \left[N\mu_{TInt}\left(\frac{\sigma_c\,(1+\sigma_c^2)^{-1}}{\mu_{TInt}\,\sqrt{\alpha}}\right)\right] - \mu_{Int}\left(\frac{\sigma_c\,(1+\sigma_c^2)^{-1}}{\mu_{TInt}\,\sqrt{\alpha}}\right)$$

$$\frac{\hat{N}' - \left(\dfrac{\sigma_c\,(1+\sigma_c^2)^{-1}(\mu_1+\mu_2)}{\mu_{TInt}\,\sqrt{\alpha}}\right) + \mu_{Int}\left(\dfrac{\sigma_c\,(1+\sigma_c^2)^{-1}}{\mu_{TInt}\,\sqrt{\alpha}}\right)}{1+\mu_{TInt}\left(\dfrac{\sigma_c\,(1+\sigma_c^2)^{-1}}{\mu_{TInt}\,\sqrt{\alpha}}\right)} \leq N. \tag{51}$$

Similar steps will find the upper bound of the confidence interval, which is

$$N \leq \frac{\hat{N}' + \left(\dfrac{\sigma_c\,(1+\sigma_c^2)^{-1}(\mu_1+\mu_2)}{\mu_{TInt}\,\sqrt{\alpha}}\right) - \mu_{Int}\left(\dfrac{\sigma_c\,(1+\sigma_c^2)^{-1}}{\mu_{TInt}\,\sqrt{\alpha}}\right)}{1-\mu_{TInt}\left(\dfrac{\sigma_c\,(1+\sigma_c^2)^{-1}}{\mu_{TInt}\,\sqrt{\alpha}}\right)}. \tag{52}$$

As an additional conservative measure, the lower bound of the confidence interval should be truncated to the next lowest integer, and the upper bound should be rounded to the next highest. In continuation and conclusion of the example, we will use Equations 46, 51 and 52, with, since our target was classified as a Vehicle, $\mu_{Int} = 50$ and $\mu_{TInt} = 58$, to find

$$\frac{5 - \left(\dfrac{0.067(65+65)}{58\,\sqrt{0.1}}\right) + 50\left(\dfrac{0.067}{58\,\sqrt{0.1}}\right)}{1+58\left(\dfrac{0.067}{58\,\sqrt{0.1}}\right)} \leq N,$$

and

$$N \le \frac{5 + \left(\frac{0.067\,(65+65)}{58\,\sqrt{0.1}}\right) - 50\left(\frac{0.067}{58\,\sqrt{0.1}}\right)}{1 - 58\left(\frac{0.067}{58\,\sqrt{0.1}}\right)},$$

which yields the 90% confidence interval that

$$(3 < N < 7).$$

V. CONCLUSIONS

A. SUMMARY

1. Current Sensor Parameters

It is clear that the values currently used by the Sensor Formula for average detection distance are in error. The experiment that was conducted shows that the values actually experienced by operators using the TRSS system are much, much less than those stated in the Operator's Manual. Nonparametric tests on the data confirm this. Although only one soil type was tested in this experiment, previous work has shown that the detection distance will vary by soil type. The experiment also confirmed that detection distance is also affected by target class, and that in the case of the Wheeled class, it may also be affected by different vehicle types.

Most surprising of all was the implication that most of the variance in detection distance was inherent in TRSS itself. Theoretically, a single, stationary geophone should detect the seismic signature of a moving target at a generally uniform distance, especially if the target approaches the sensor from the same direction and at the same velocity. Not only was it found that there was a great deal of variation between sensors detecting the same target, but that there was a great deal of variation in the detection distances of the same sensor. Neither the slight variations in target velocity, nor the possibility of environmental noise, were enough to explain the large range of detection distances experienced.

It is suspected that the variation is due to the delay times built into TRSS itself. However, the sensors could not be tested separately from the monitoring system. Perhaps this explains the difference between these results, and those experienced by the Waterways Experiment Station. Their experiment used SID data filtered through scientific monitoring equipment, and had the benefit of scientific geophones to use as comparisons. Nevertheless, the SMS is the system which is used operationally to monitor the sensors, so the sensor parameters must be defined as they are interpreted by that system.

The table below provides the recommended sensor parameters, for the target classes indicated, when the targets are moving cross country over fine, sandy soils.

Recommended Sensor Parameters				
	Low Sensitivity		Medium Sensitivity	
Target Class	μ	σ	μ	σ
Personnel	18	18	25	15
Wheeled	35	15	65	20
Tracked	120	30	175	35
All values given in meters.				

Table 9. Recommended Sensor Parameters.

2. Current Classification Rule

The danger in classifying targets based on a simple rule is obvious. There are many situations in which vehicles may move slower than 9 kph, but, as it currently stands, TRSS will never detect them. The current rule can be improved to take into account slow moving vehicles. The use of Bayes' Rule is common to classification problems, and even REMBASS uses a version of it. The sensor parameters have a small impact on this rule, since in even the most extreme cases, the variance of the velocity estimate is very small. It can be reduced even further, through the use of additional strings of seismic sensors, or by including infrared sensors into the algorithm. Further study needs to be done on the distribution of velocity given target type and movement conditions, but data on the distributions could be collected from almost any major military exercise.

The classification rule presented in Chapter IV also provides the Intelligence specialist with a method to evaluate the strength of his classifications. The simple posterior risk calculation will give him a measure of how likely misclassification is, and, if he desires a more sophisticated measure, establishing a loss function for misclassification can provide insight into how dangerous it might be to incorrectly classify a target. In any event, it provides him with more information than does the current method.

3. Current Sensor Formula

It has been shown that all formulas currently used are positively biased. The largest bias is experienced when Tracked targets are detected, as they generate the highest variation in R. In the worst case, using two sensors on their medium setting placed 300 meters apart, the bias correction factor $1+\sigma^2_c$ is only equal to 1.0131. It is suggested that sensors be placed no less than 300 meters apart. However, even if they were placed 100 meters apart, the bias correction factor would still only be 1.1179.

As previously mentioned, the most significant improvement occurs when proper sensor parameters are used, especially for CDR, which is always subtracted from the observations to yield the length estimate. One of the most frequent complaints about the current model is that it often drastically underestimates the column length. That is not surprising, given that, for example, the CDR for tracked vehicles in the Operator's Manual is 600 meters, while this study suggests that it should only be 350 meters.

One of the most glaring errors in the current model is that it ignores variance in sensor capabilities. It is clear, from the results of the experiment, that there is a great deal of variance in their capabilities, and that it does affect the SMS's ability to describe targets. The revised model offered here, provides an analytical solution to this problem, and, when combined with the experimental results, provides a tool which can be applied immediately to enhance the target description algorithms. In addition to enhancing the ability of the SMS to make point estimates, for the first time a method is provided to place a confidence interval around that estimate. This step, by itself, will improve the utility of TRSS. Now the users will have a conservative estimate, based on Chebyshev's inequality, of how good the information they are getting really is.

A simple modification, which reduces the variation in the column length and number of elements estimates, is the use of the observation TT, instead of $TT1$. This measure reduces the variation by a factor of 2, and requires no additional computational power.

The issue of computational power is central to the sensor problem. Up until Phase V, many of the sensor calculations were performed by hand, and equations as complicated as those presented here were not readily usable. However, the Phase V SMS uses RISC based computers to interpret the sensor messages and to perform all calculations, and the methods presented here now become trivial. In those remote cases where the algorithms must still be performed manually,

the old formula will still provide acceptable answers, but only as long as the correct sensor parameters are used. Even in those cases, use of *TT* will still serve to reduce variance.

Finally, it has been shown that the number of elements estimate can be enhanced by calculating the average interval differently. Including the average length of an element, as well as the average interval between elements, provides more accurate information. Data regarding the length of vehicles is readily available, and the average interval is discernible from many doctrinal publications.

B. RECOMMENDATIONS

1. More Sensor Experiments

The experiments conducted as part of this study were restricted by resources to a limited number of target types, a single velocity per target type, and to a single soil type. In a sense, the variation observed in a single configuration of the experiment can be attributed only to the time delays inherent to TRSS, because each target class traveled at a unique velocity, so the individual effects of those two factors can not be estimated. In order for the Marine Corps to construct a database of sensor parameters which will be usable worldwide, more data should be collected.

a. Format

Future experiments should be conducted so that both the arriving and departing detection distances can be observed. Equation 4 provides the method for calculating the arriving detection distance. The following equation will calculate the departing distance:

$$r_{ij} = \sqrt{(h_i)^2 + (v_j\,[t_{j2} - t_{j0}] - l)^2}\,, \tag{53}$$

where t_{j2} is the last time the sensor activated, and l is the length of the target (wheelbase, if only a single vehicle is used). More accurate observations on t_{j0} may be collected if infrared sensors are placed to record the time the target passes each seismic sensor. Placing the sensors within one to three meters of the test track will ensure that any extremely short detection distances are recorded.

b. Treatments Desired

In addition to data regarding the overall effects of differing soil types and target classes on general sensor performance, it is also necessary to collect data on the variance between individual sensors. Once basic parameters have been established, convoy targets and columns of mixed target classes should be investigated to determine the detection capabilities against mixed targets. A full analysis of variance could be carried out for each experiment, to determine which factors have the most impact on sensor capabilities. It is relatively inexpensive to conduct detection distance experiments, and it would enhance a SCAMPs operational capability if they knew the individual parameters of each of their sensors.

2. Implement Revisions

The following section contains specific recommendations to enhance the Sensor Formula and TRSS capabilities.

a. CDR

Replace the values for average detection radius in the current Operator's Manual with more realistic figures. Reports from users, and the results of this experiment, indicate that they are in error. Presently, the Sensor Formula consistently underestimates length and number of elements because of these distances. Conduct additional tests to determine the effects of other soil types and velocities on the sensor parameters.

b. Classification Rule

Conduct additional investigations to determine the velocity distributions for the various target classes, then implement the classification rule given in Equation 28. Provide additional training to Intelligence personnel so that they can better estimate the *a priori* distribution of target classes.

c. TT vs TT1

Use the variable TT, as given in Equation 13, in place of $TT1$. This requires only a very slight modification to the current SMS program, and by itself, will reduce the variance of $\hat{LC}'$ by a factor of 2.

d. *Sensor Formulas*

As soon as sufficient data has been collected and analyzed, replace the current sensor formulas with those found in Equations 19, 35, and 46. Given the sample variances experienced in this experiment, adjustment due to the use of the bias correction factors will be slight, but if a combination of effects is found for which the variance is much greater, the effect may be drastic.

e. *Message Format*

Revise the current Sensor Report format so that it states the posterior distribution of target classes, as well as the target description for each class. The target description should include the confidence intervals, and the associated probabilities, for all estimates given. These measures of how good the estimates are, often provide as much information as the estimates themselves.

f. *IRID Reliability*

The failure rate of the IRIDs was unacceptable, especially considering the benign environment in which they were employed. They also require operational testing. As it is, it appears that the SIDs provide more reliable information than did the IRIDs, and at much less the cost.

g. *T_i from data, not screen*

The errors inherent to SMS are bad enough, without inducing additional operator errors. The screen resolution of the SMS is too low to rely on operator's ability to measure cursor location to determine *TT* and *Tm*. The SMS interface should be modified so that it extracts the observed times directly from the sensor message data base.

C. CONCLUSION

The objective of this study was to determine if the current sensor algorithm could be improved, and to suggest enhancements that would provide better information to the operational commander. It has been found that the Sensor Formula can, indeed, be improved, especially in

light of the sophistication of TRSS Phase V, and can again become an important, and trusted, tool in the Intelligence analysts toolbox.

LIST OF REFERENCES

1. Waterways Experiment Station, U.S. Army Corps of Engineers, *Analysis of Seismic Intrusion Detector (SID) Portion of Tactical Remote Sensor System (TRSS)*, Vicksburg, MS, July, 1993.

2. Hester, Milton J., *Investigation into the Attenuation of Seismic Impulses in Different Soil Types*, Master's Thesis, Naval Postgraduate School, Monterey, CA, March, 1972.

3. ENSCO, Inc., *Target Classification Algorithm Development for a Tactical Battlefield Sensor,* Springfield, VA, 20 May, 1983.

4. United States Marine Corps, *Sensor Operators Handbook*, MCDEC, Quantico, VA, 1989.

5. United States Marine Corps, *Fleet Marine Force Manual 3-22-3 for the Sensor Control and Management Platoon (Draft)*, MCCDC, Quantico, VA, January, 1993.

6. United States Marine Corps, *Tactical Remote Sensor System Phase V Operator's Course*, MCCDC, Quantico, VA, December, 1992.

APPENDIX A. THE TACTICAL REMOTE SENSOR SYSTEM

[Extracted from TRSS Operator's Course (Ref. 6).]

INTRODUCTION TO THE TACTICAL REMOTE SENSOR SYSTEM (TRSS) PHASE V

1. In order to effectively employ the TRSS, we need to gain a working knowledge of the equipment's characteristics/capabilities, and what equipment makes up the system. TRSS Phase V consists of a suite of remotely monitored, unattended ground sensors that detect activity, relays that provide a long range data transmission capability, and monitors that receive and display the data. In the TRSS Phase V, target detection is accomplished primarily with seismic sensors. Confirming sensors are used to assist in verifying target presence and in identifying target characteristics. The Phase V Tactical Remote Sensor System provides:

Continuous, all weather detection
Location determination
Activity monitoring in a given area
The ability to use a variety of emplacement & detection techniques
Monitoring of hostile & friendly movements
A capability to record data that can be stored/evaluated at later date.

a. What is the AN/GSQ-257 Unattended Ground Sensor Set (UGSS)? What equipment makes up the set? The UGSS is a suite of unattended sensors that detect activity through use of various techniques. They transmit data to a Relay, Portable Monitor (PM), or Signal Data Recorder (SDR). Except for the ADSID, all the UGSS units are manpacked and hand emplaced. The ADSID is emplaced from helicopters or fixed wing aircraft. The following terms are used throughout the TRSS Phase V and must be understood by equipment operators. The UGSS uses detectors to sense target activity. When coupled to an ETU and a cable, these detectors make up a "sensor". Therefore, the term "sensors is used to indicate both a target detection and a message transmission capability. Thus, a detector, cable, and ETU, are termed a "sensor" or "sensor set" because, when they are electronically coupled together, they provide a complete target detection

and message transmission capability. The sensor messages may be remotely monitored through several methods.

b. The following is the AN/GSQ-257 UGSS Equipment:

Seismic Intrusion Detector (SID)
Infrared Intrusion Detector (IRID)
Auger
Tripod
Magnetic Intrusion Detector (MAGID)
Air Delivered Seismic Intrusion Detector (ADSID)
ADSID Practice Round
Encoder Transmitter Unit (ETU)
Sensor Cable

c. The following is the additional equipment that is included in the Tactical Remote Sensor System (TRSS):

Relay
Portable Monitor (PM)
Sensor Mobile Monitor System (SMMS)
Sensor Monitor System (SMS)

2. Encoder Transmitter Unit (ETU). All of the detectors, except the ADSID, require an external transmitter to encode and transmit the sensor data. An Encoder Transmitter Unit (ETU) was developed specifically for this purpose. The ETU is used in conjunction with the hand-emplaced sensors.

CHARACTERISTICS OF THE ETU:

The ETU is a hand carried, sealed unit that provides encoding and transmission functions for the detectors that sense various physical phenomena. It is small (length 5.88 in/width 5.55 in/ height 3.38 in), lightweight 4.0 lbs. with batteries), and simple to program/setup for field use.

FUNCTIONS OF THE ETU:

The ETU accepts input signals (raw activation data) from the connected detectors (SID, MAGID, IRID), processes and encodes the data according to TRSS message format, and transmits the sensor messages. The main function of the ETU is to be the data Encoder/Transmitter and the power source for the SID, MAGID, and IRID. The ETU utilizes an omni-directional antenna (with a right angle connector). In order to properly function, the uninsulated portion of the antenna must be kept above the ground. In addition to transmitting sensor messages, the ETU transmits a state-of-health message approximately every 22 minutes to inform the monitoring activity that it is still in an operating condition. The ETU also has the ability to advise monitoring activities that it being moved or tampered with. If the ETU is tilted more than 30 degrees (tampering), it will send a tilt message, rather than a proper sensor message, every 12 seconds. These messages will continue until the ETU is shut down, righted and reset. If the ETU is righted, but not properly reset, it will send tilt messages when further activations occur.

CAPABILITIES OF ETU:

The ETU is a battery powered unit that receives activation data from different detectors. It processes and encodes raw data into the TRSS sensor messages, and transmits the messages to monitoring equipment. The operating life of the ETU is user selectable, and ranges from 10 minutes to 60 days (based upon the life of the batteries, and the end-of-life (EOL) switch setting on the ETU). The ETU is capable of continuous operation for a minimum of 30 days in temperature ranges from -22°F to +149°F.

LIMITATIONS OF THE ETU:

The ETU's life is limited by its battery power. Its messages are susceptible to jamming, either intentionally or unintentionally. The attached detectors have no target discrimination capability (they will sense flowing water; metal objects, such as a bridge; sunlight; etc.), so the ETU will transmit messages that are based upon occurrences of environmental influence.

3. Seismic Intrusion Detector (SID). The SID is the primary hand emplaced detector in the TRSS.

CHARACTERISTICS OF THE SID:

The SID is a small (length 2.80 in/width 2.38 in/height 1.64 in), lightweight (0.6 lbs), sealed detector that reacts to minute seismic vibrations in the ground. It contains a cable receptacle and a sensitivity switch with ranges of LOW, MEDIUM, and HIGH.

FUNCTIONS OF THE SID:

The function of the SID is to detect seismic vibrations in the ground and send signals to the ETU when certain vibration levels are detected.

CAPABILITIES OF THE SID:

The SID is capable of detecting minute seismic vibrations in the ground and sending a pulse (signal) to the ETU for processing.

LIMITATIONS OF THE SID:

The SID depends upon the ETU for its power. The SID contains no discrimination circuitry and will therefore react to incidents of environmental influence such as heavy rains, high winds, aircraft generated vibrations, etc.

4. Infrared Intrusion Detector (IRID).

CHARACTERISTICS OF THE IRID

The IRID is a small (length 5.52 in/width 3.38 in/height 1.91 in, lightweight (1.2 lbs), sealed detector that reacts to changes in temperature relative to a constant ambient background. It detects motion left-to-right and right-to-left, dependent upon the portion of the field of view that the target first entered. The IRID contains a cable receptacle and a sensitivity switch (containing HIGH, LOW, and STANDBY settings).

FUNCTIONS OF THE IRID:

The IRID is a confirming detector that senses changes in ambient temperature within its field of view relative, to the constant background temperatures. It confirms direction based upon the portion of the field of view that was entered first, and it can be used in determining target count. It sends this information to the ETU for further processing.

CAPABILITIES OF THE IRID:

The IRID is capable of detecting minute changes in temperature within its field of view, relative to the constant background temperatures. It can also be used in counting the number of objects passing through its field of view. The IRID then reports this activity to the ETU for further processing and sensor message transmission.

LIMITATIONS OF THE IRID:

The IRID depends upon the ETU for its power. The IRID has no discrimination capability; therefore, it cannot distinguish the difference between vehicles, personnel or animals that pass through its field of view.

5. Magnetic Intrusion Detector (MAGID).

CHARACTERISTICS OF THE MAGID:

The MAGID is a small (length 6.10 in/width 2.50 in/height 1.57 in), lightweight (0.9 lbs), sealed, dual axis magnetometer that detects changes in the earth's magnetic field. These changes are caused by the movement of ferromagnetic materials, such as, vehicles or personnel carrying weapons. (NOTE: The MAGID can be effected by the presence of ferromagnetic materials whether they are moving or stationary. This is an important consideration in the emplacement of the MAGID.) The MAGID can distinguish the difference between targets moving from left-to-right or from right-to-left within its detection radius. The MAGID contains a cable receptacle and a sensitivity switch (containing HIGH, LOW and STANDBY settings).

FUNCTION OF THE MAGID:

The MAGID is a confirming type detector that detects changes in the earth's magnetic field caused by the movement of ferromagnetic materials within its detection radius.

CAPABILITIES OF THE MAGID:

The MAGID is capable of detecting ferromagnetic materials by sensing changes in the earth's magnetic flux lines within its detection radius. Determination of the direction of movement, relative to the MAGID, is accomplished by a dual axis magnetometer.

LIMITATIONS OF THE MAGID:

The MAGID is dependent upon the ETU for its power. The MAGID contains no target discrimination capability. It will therefore react to environmental influences such as lightning,

electrical transmission lines (whether buried or overhead), and other events which cause magnetic flux line variations.

(NOTE: Water lines are unique in that they will affect both the SID (flowing water in pipes), and the MAGID (metal pipes).)

6. Air Delivered Seismic Intrusion Detector (ADSID)

CHARACTERISTICS OF THE ADSID:

The ADSID is an aircraft delivered, ballistically packaged, self contained, seismic sensor that detects minute vibrations in the ground. It is a "dart-shaped" device designed to penetrate the earth upon impact, leaving its antenna above ground level. The ADSID has its own power, detection, encoding and transmission capabilities. The ADSID contains controls for setting its detector sensitivity, sensor identification number, transmission channel and end-of-life setting. The ADSID itself is a true "sensor", since it contains both a detector and a transmitter.

FUNCTION OF THE ADSID:

The function of the ADSID is to detect minute seismic vibrations in the ground caused by vehicles or personnel. It also provides a state-of-health message approximately every 22 minutes to inform the monitoring personnel of its operational condition.

CAPABILITIES OF THE ADSID:

The ADSID is capable of being delivered by various aircraft, such as, fixed wing, rotary wing, and unmanned aerial vehicles. The ADSID can detect minute seismic vibrations in the ground, process and encode this information, and transmit sensor messages. The ADSID sends a state-of-health message approximately every 22 minutes to inform monitoring personnel of its condition and can

be programmed for a specific end-of-life or shut-down time (from 2 to 30 days in two day increments).

LIMITATIONS OF THE ADSID:

The ADSID's operating life is limited by its battery power. The ADSID is a ballistic penetration device that can be damaged by striking rocks, tree limbs, etc., during implant operations. The ADSID has no target discrimination capability, and it will detect and report environmental seismic events that may not be of interest to the sensor monitoring personnel.

7. Sensor Cable. The Sensor Cable is a flexible multi-conductor cable that couples either the SID, IRID or MAGID to the ETU. This cable provides power to the detector(s) and carries sensor activation data to the ETU for encoding and transmission. The Sensor Cable is hand emplaced in the ground and is waterproof.

8. AN/USQ-121 Portable Monitor (PM). The Portable Monitor is a hand-held, portable Radio Frequency (RF) receiver/display unit. The PM receives, demodulates, and decodes sensor messages. It displays the sensor identification number (ID) and a sensor message symbol on any one of the 599 TRSS Phase V message channels. It also provides an adjustable audio tone that "beeps" when messages are received. The PM is used primarily to confirm the proper operation of the sensors, and to determine the detection radii of the detectors during sensor implant. It monitors sensor activation responses by displaying the sensor ID and message symbol, whenever a valid message is decoded. The unit can also indicate that alarm messages are received from the United States Army's Remotely Monitored Battlefield Sensor System (REMBASS) sensors.

9. RE-1162/U Relay Assembly. The Relay is a multiple channel, Very High Frequency (VHF) and/or Ultra High Frequency (UHF) communications receiver/relay. The Relay extends the range of the TRSS sensors, and it enables communications between sensors and monitors when communications via line-of-sight is prevented by terrain. The Relay can operate in both real-time and non-real-time modes, and it can be remotely commanded to change modes, channels, etc., after

emplacement. One or more CY-8680/G Battery Boxes are required for operation of the Relay. These Battery Boxes may be piggy-backed together to extend the Relay's operating life. (NOTE: THE UHF TRANSMISSION CAPABILITY IS NOT A CURRENT CAPABILITY OF THE RELAY.)

10. AN/MSC-XXX Sensor Mobile Monitor System (SMMS). The SMMS is a mobile monitoring station for receiving, processing, storing, retrieving, and displaying TRSS sensor activation data. It consists of a Sensor Monitor System (SMS), AN/USQ-66B(V), mounted on a High Mobility Multi-purpose Wheeled Vehicle (HMMWV). The SMS is environmentally controlled and houses the equipment required to receive and process the TRSS message data. The equipment contained within the SMS includes two RO-376B/USQ Signal Data Recorders (SDR), two VGA color monitors that are used to display sensor activation data and video images, and two 24 pin dot matrix printers for data analysis, report preparation, and video image printing. In its eight channel configuration, the SMS can monitor, decode and display 1,008 sensors in the TRSS Phase V, or the US Army's Remotely Monitored Battlefield Sensor System (REMBASS) formats. In its normal operating mode, a self contained, diesel powered generator provides power for the SMS equipment, including the environmental control unit. The SMS can also be powered by 120/208 VAC, 3-phase commercial power, or by 120 VAC 60 Hz single phase power (120 VAC power will not operate the environmental control unit, however).

11. Technical Characteristics of the Tactical Remote Sensor System.

Frequency Range	The TRSS operates in the 138 - 153 MHz frequency range.
Channel Spacing	Each channel within this frequency range is spaced 25 kHz apart.
Number of channels	The total number of frequencies available within this bandwidth is 599.

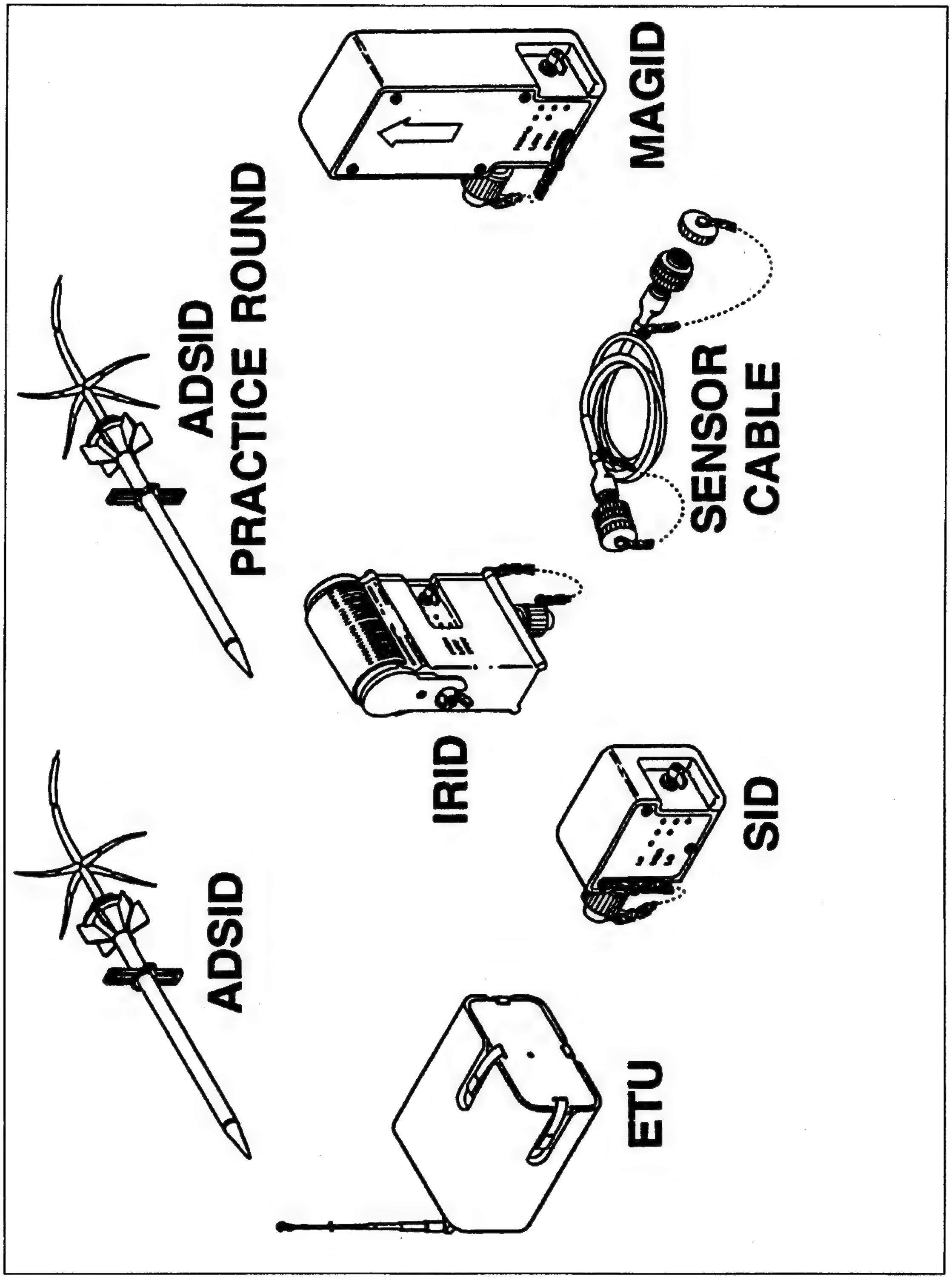
Operating Temperature Range	The operating temperature range for the TRSS Phase V is from -22° F (-30° C) to + 149° F (+65° C)
Operating Altitude	The altitude parameters for the TRSS is from O feet above mean sea level (AMSL) to 15,000 feet AMSL.
Message Type	The TRSS uses a standard 20 or 29 BIT message format.

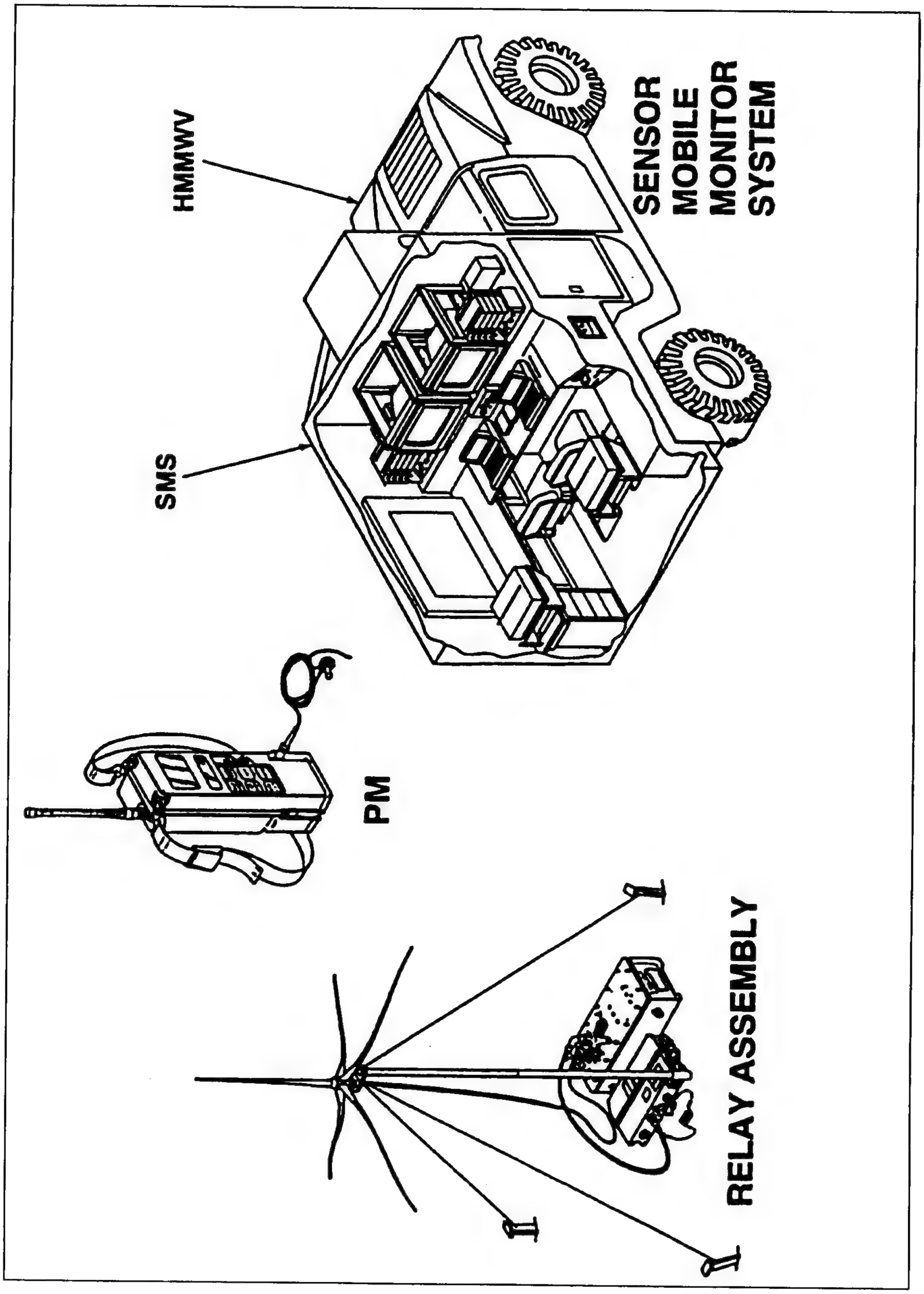
The TRSS equipment requires radio frequency line-of-sight (direct or relayed).

REFERENCES:

1. FMFM 3-22-3
2. TM 07754B-10
3. TM 07726B-10
4. TM 09632A-14&P
5. TM 08236B-10

TRSS Components:




HMMWV
SMS
SENSOR
MOBILE
MONITOR
SYSTEM
PM
RELAY ASSEMBLY

APPENDIX B. FUNCTIONS OF DETECTION DISTANCE

The TRSS Sensor Management System (SMS) reports seismic sensors activations by recording the time at which the sensor's Encoder Transmitter Unit (ETU) sent the activation message. The activation messages from a single sensor will always be at least 12 seconds apart, even if the sensor is continuously activated, due to an inhibit time built into the ETU. The times reported by a sensor, T_i, and the functions of the reported times, *Tm* and *TT*, are functions of the sensor's detection radius, the target's velocity, the target's length, and the distance between reporting sensors. Figure 18 depicts the relationships between the T_i, the *R*, and the sensors, and serves as a reference for the rest of this appendix.

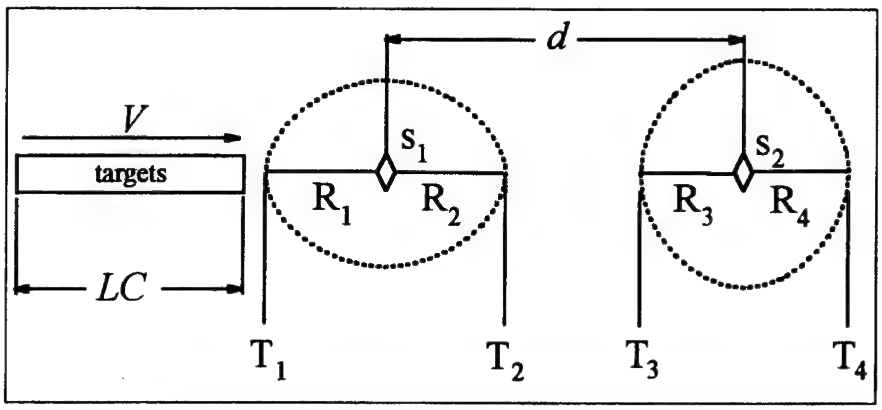


Figure 18. Sensor Observations and Their Relation to Detection Distances.

Throughout this problem, target columns are assumed to be moving in a direction parallel to a line drawn through the positions of the two sensors, and sufficiently close to that line so that their distance away from the line does not affect the sensor observations. The variables and parameters are defined as follows:

d	distance between the sensors.
LC	length of the target column. Assumed to be constant throughout the detection period.
R_1	detection distance of the first sensor, against an approaching target.
R_2	detection distance of the first sensor, against a departing target.
R_3	detection distance of the second sensor, against an approaching target.

R_4	detection distance of the second sensor, against a departing target.
s_1	location of the first sensor.
s_2	location of the second sensor.
T_1	time target is first detected by the first sensor.
T_2	time target is last detected by the first sensor.
T_3	time target is first detected by the second sensor.
T_4	time target is last detected by the second sensor.
V	velocity of the target column. Assumed to be constant throughout the detection period.

A. T_i AS A FUNCTION OF R_j

All times are expressed in minutes. The detection period begins when the target is first observed by the sensors. This is defined to be T_1. T_1 serves as the base time for all other observations. Therefore, using the time-distance-velocity relationship, the other observed times are as defined below.

$$T_2 = T_1 + \frac{R_1 + R_2 + LC}{V}. \tag{54}$$

$$T_3 = T_1 + \frac{R_1 + d - R_3}{V}. \tag{55}$$

$$T_4 = T_1 + \frac{R_1 + d + R_4 + LC}{V}. \tag{56}$$

Now the functions of observed time, which are required for target classification and description, can be defined in terms of the sensor capabilities and the true state of the target.

B. *Tm* AS A FUNCTION OF R_j

Tm is defined as the time required by the target to move from a point adjacent to s_1 to a point adjacent to s_2. This distance is defined as d, and is recorded when the sensors are placed. The operators know this distance when they use the Sensor Formula. All length values are expressed in terms of meters.

$$Tm = \left[T_3 + \left(\frac{T_4 - T_3}{2}\right)\right] - \left[T_1 + \left(\frac{T_2 - T_1}{2}\right)\right]$$

$$= \frac{T_4 + T_3 - T_2 - T_1}{2}$$

$$= \tfrac{1}{2}[\left(T_1 + \frac{R_1 + d + R_4 + LC}{V}\right) + \left(T_1 + \frac{R_1 + d - R_3}{V}\right)$$

$$-\left(T_1 + \frac{R_1 + R_2 + LC}{V}\right) - (T_1)]$$

$$= \frac{R_1 - R_2 - R_3 + R_4 + 2d}{2V}. \tag{57}$$

Equation 57 serves as the basis for the velocity estimate, $\hat{V}'$, and also plays an important role in the column length estimate, $\hat{LC}'$. The expectations of this random variable are required for both estimates. It is assumed that the both the arriving and departing *Rj* for the same sensor are identically and independently distributed random variables. Furthermore, the distributions of the *R* corresponding to s_1 are independent of those corresponding to s_2. Recalling that *V* is constant during any given observation period, this implies that

$$E[Tm] = \frac{d}{V}, \tag{58}$$

and

$$Var(Tm) = \frac{\sigma_1^2 + \sigma_2^2}{2V^2}, \tag{59}$$

where σ_k^2 is the variance of the *R* pertaining to s_k. If both sensors are placed in the same soil composition and set at the same sensitivity setting, the distributions are also identical, and therefore the variance reduces to

$$Var(Tm) = \frac{\sigma_1^2}{V^2}. \tag{60}$$

C. *TT* AS A FUNCTION OF *R*

TT is defined as the mean total time the target is detected by the sensors. In the old Sensor Formula, only the total detection time of one sensor was used, and this was called *TT*1. However, use of the mean detection time is a variance reduction technique, which will improve our estimation of the target column length. *TT* replaces *TT*1 in all sensor calculations. *TT* is defined as

$$\begin{aligned} TT &= \frac{(T_2 - T_1) + (T_4 - T_3)}{2} \\ &= \tfrac{1}{2}\Big[\Big(T_1 + \frac{R_1 + R_2 + LC}{V}\Big) - (T_1) + \Big(T_1 + \frac{R_1 + d + R_4 + LC}{V}\Big) \\ &\quad -\Big(T_1 + \frac{R_1 + d - R_3}{V}\Big)\Big] \\ &= \frac{R_1 + R_2 + R_3 + R_4 + 2LC}{2V}. \end{aligned} \tag{61}$$

Recall that both LC and V are considered to be constant throughout the period of observation. The expected value of TT is

$$E[TT] = \frac{\mu_1 + \mu_2 + LC}{V}, \tag{62}$$

where μ_k is the mean of the R pertaining to s_k, and its variance is

$$Var(TT) = \frac{\sigma_1^2 + \sigma_2^2}{2V^2}, \tag{63}$$

where σ_k^2 is the variance of the R_j pertaining to s_k. Note that Var(TT) = Var(Tm). This will be very useful when determining the estimates of V and LC. If both sensors are on the same sensitivity setting, the expected value becomes

$$E[TT] = \frac{2\mu_1 + LC}{V}, \tag{64}$$

and the variance becomes

$$Var(TT) = \frac{\sigma_1^2}{V^2}. \tag{65}$$

D. *TT / TM* AS A FUNCTION OF *R*

The variable $\frac{TT}{Tm}$ is the basis for the column length estimate. As a function of the R, and with respect to the target characteristics, Equations 57 and 61 show that this variable can be expressed as

$$\frac{TT}{Tm} = \frac{R_1 + R_2 + R_3 + R_4 + 2LC}{R_1 - R_2 - R_3 + R_4 + 2d}. \tag{66}$$

Since this is a nonlinear function of the R, the expectations of the function can not simply be expressed as the function of the individual expectations. Chapter IV provides detail about the use of the propagation of errors method in determining the expected value and variance of this ratio.

APPENDIX C. DISTRIBUTIONS OF TARGET VELOCITY

The target classification method used by the revised sensor formula requires prior knowledge of the distribution of target velocity, given target class. No previous studies of these distributions were found, so it was decided to conduct an initial investigation as an adjunct to the study of the sensor formula. The method used to collect data from which to estimate the distributions was a survey of experienced personnel. A preferable method would have been to observe how fast columns actually move under operational conditions, but the assets to collect such observations were unavailable.

A. SURVEY

1. Methodology

A survey of US Army and Marine Corps officers with operational and tactical experience was conducted at the Naval Postgraduate School. Each respondent was asked to provide his best estimate, based on his experience of having traveled in or organized movement columns, of how often a column of a particular class would be expected to move in a certain velocity interval, for different movement conditions. The tactical situation was one in which enemy contact was possible, but unlikely. The column types presented were Personnel, Wheeled, and Tracked, and the movement conditions presented were Paved Road, Improved Road, Unimproved Road, and Cross Country. Each officer was asked to estimate the number of occurrences, out of 100 total, that the column would be moving at each velocity.

2. Results

Once collected, the data represented the respondents estimates of the probability, p_i, that the velocity would fall into a specific velocity interval Vel_i. Using this method, the distribution velocity, given target type and movement condition, is a multinomial distribution. The maximum likelihood estimate for each p_i was formed by the ratio of occurrences for a given interval with the total number of occurrences, and the results for each combination are tabulated below. Only 21 responses were received, so this study only offers basic insight into the true distributions. No confidence levels or goodness of fit tests were conducted on this data because of this.

B. PAVED ROADS

This movement condition describes movement on a paved concrete or asphalt surface, under clear, dry, daylight conditions. The terrain was considered to be rolling hills, with no steep ascents or descents. The wheeled column was described as a uniform mixture of heavy and light vehicles. The tracked column was described as a uniform mixture of tanks and armored personnel carriers. The personnel column was described as a column of 200-300 individual, moving in a staggered column. The results are provided in Table 10, and the shapes of the distributions can be seen in Figures 19 through 21. Velocity intervals are given in terms of miles per hour.

Pr(V|TC) -- Paved Road			
Velocity Interval	**Target Class**		
	Personnel	**Wheeled**	**Tracked**
0-2	0.1400	0.0005	0.0005
2-4	0.4754	0.0000	0.0000
4-6	0.3043	0.0005	0.0005
6-8	0.0744	0.0005	0.0031
8-10	0.0095	0.0014	0.0302
10-15	0.0000	0.0124	0.0599
15-20	0.0000	0.0438	0.0938
20-25	0.0000	0.0671	0.1901
25-30	0.0000	0.0929	0.2120
30-35	0.0000	0.1248	0.1875
35-40	0.0000	0.1514	0.0990
40-45	0.0000	0.2367	0.0922
45-50	0.0000	0.1738	0.0313
50-55	0.0000	0.0624	0.0000
55-60	0.0000	0.0262	0.0000
60-65	0.0000	0.0052	0.0000
65-70	0.0000	0.0005	0.0000
70-75	0.0000	0.0000	0.0000
75-80	0.0000	0.0000	0.0000

Table 10. Target Velocity Distributions -- Paved Roads.

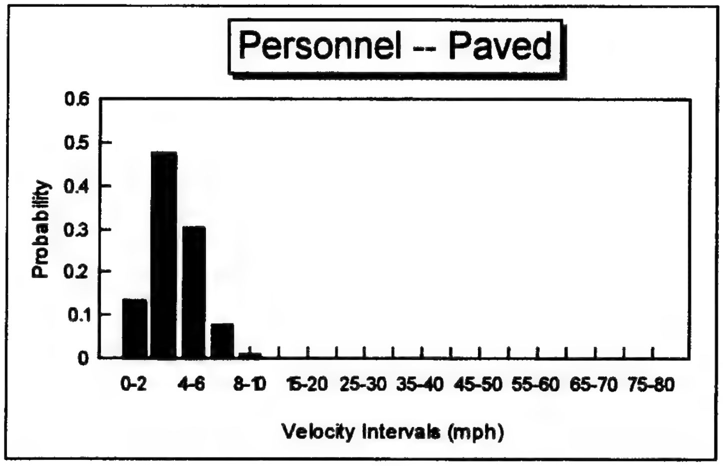


Figure 19. Velocity Distribution: Personnel Target, Paved Road.

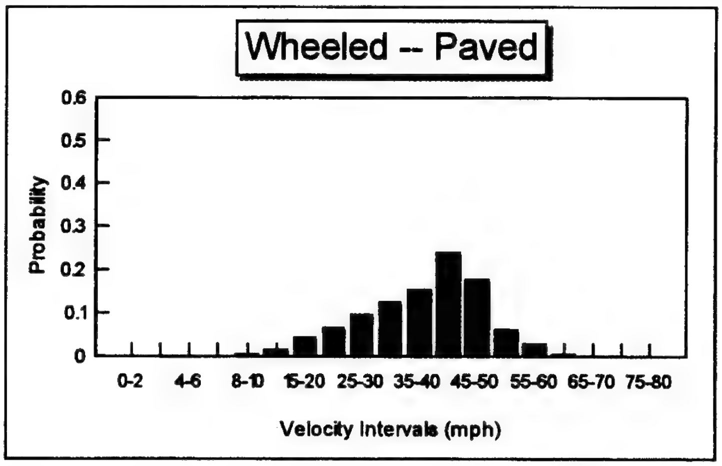


Figure 20. Velocity Distribution: Wheeled Target, Paved Road.

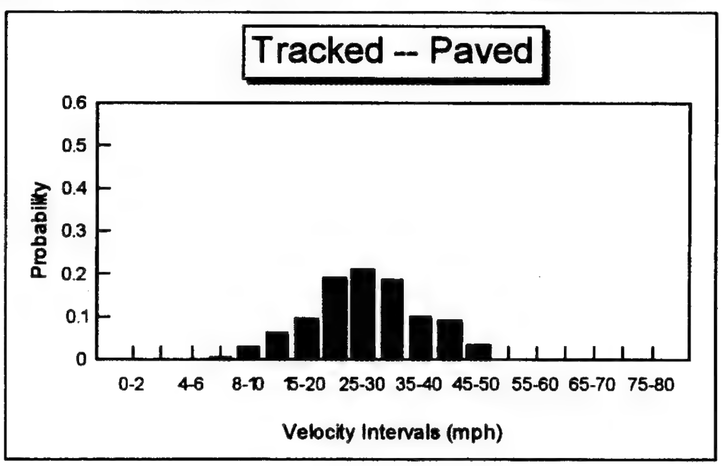


Figure 21. Velocity Distribution: Wheeled Target, Paved Road.

C. IMPROVED ROADS

This movement condition describes movement on a graded gravel or packed clay surface, under clear, dry, daylight conditions. The terrain was considered to be rolling hills, with no steep ascents or descents. The wheeled column was described as a uniform mixture of heavy and light vehicles. The tracked column was described as a uniform mixture of tanks and armored personnel carriers. The personnel column was described as a column of 200-300 individual, moving in a staggered column. The results are provided in Table 11, and the shapes of the distributions can be seen in Figures 22 through 24. Velocity intervals are given in terms of miles per hour.

$Pr(V \vert TC)$ – Improved Road			
Velocity	Target Class		
Interval	Personnel	Wheeled	Tracked
0-2	0.2000	0.0005	0.0005
2-4	0.5332	0.0000	0.0000
4-6	0.2294	0.0029	0.0058
6-8	0.0374	0.0081	0.0178
8-10	0.0033	0.0310	0.0541
10-15	0.0000	0.0667	0.1024
15-20	0.0000	0.0895	0.1549
20-25	0.0000	0.1333	0.1921
25-30	0.0000	0.1943	0.1654
30-35	0.0000	0.2086	0.1003
35-40	0.0000	0.1129	0.1081
40-45	0.0000	0.1081	0.0777
45-50	0.0000	0.0262	0.0157
50-55	0.0000	0.0176	0.0052
55-60	0.0000	0.0005	0.0000
60-65	0.0000	0.0000	0.0000
65-70	0.0000	0.0000	0.0000
70-75	0.0000	0.0000	0.0000
75-80	0.0000	0.0000	0.0000

Table 11. Target Velocity Distributions -- Improved Roads.

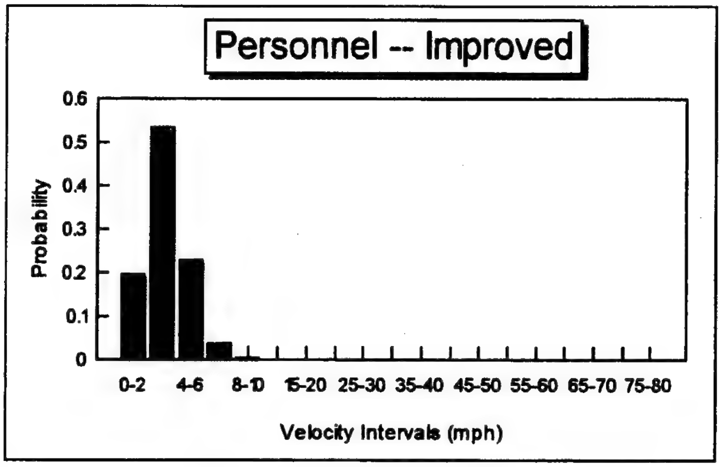


Figure 22. Velocity Distribution: Personnel Target, Improved Road.

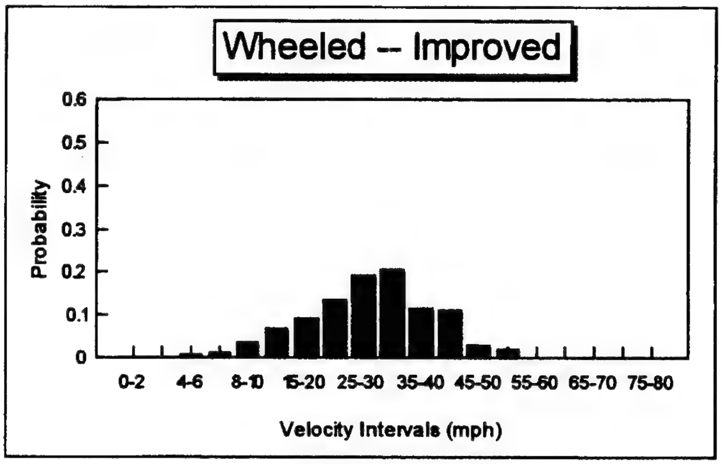


Figure 23. Velocity Distribution: Wheeled Target, Improved Road.

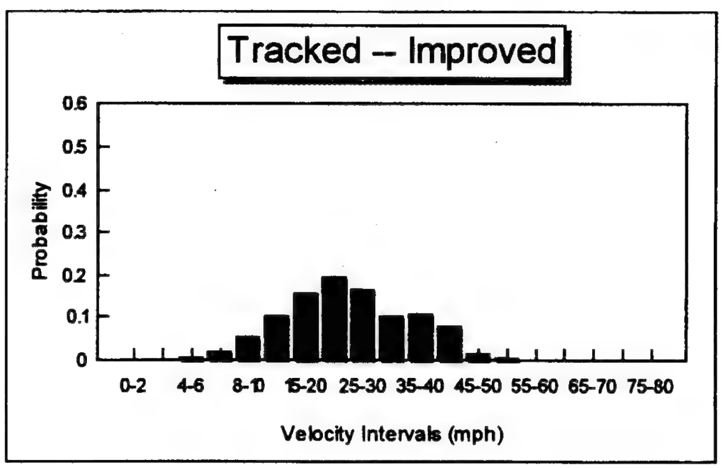


Figure 24. Velocity Distribution: Tracked Target, Improved Road.

D. UNIMPROVED ROADS

This movement condition describes movement on a loose, earthen surface under clear, dry, daylight conditions. The terrain was considered to be rolling hills, with no steep ascents or descents. The wheeled column was described as a uniform mixture of heavy and light vehicles. The tracked column was described as a uniform mixture of tanks and armored personnel carriers. The personnel column was described as a column of 200-300 individual, moving in a staggered column. The results are provided in Table 12, and the shapes of the distributions can be seen in Figures 25 through 27. Velocity intervals are given in terms of miles per hour.

$\Pr(V\mid TC)$ -- Unimproved Road			
Velocity	**Target Class**		
Interval	**Personnel**	**Wheeled**	**Tracked**
0-2	0.2500	0.0005	0.0005
2-4	0.5257	0.0010	0.0026
4-6	0.2009	0.0062	0.0100
6-8	0.0220	0.0297	0.0383
8-10	0.0047	0.0708	0.0971
10-15	0.0000	0.1053	0.1391
15-20	0.0000	0.1890	0.2178
20-25	0.0000	0.1962	0.1732
25-30	0.0000	0.2033	0.1144
30-35	0.0000	0.1081	0.0997
35-40	0.0000	0.0565	0.0504
40-45	0.0000	0.0273	0.0488
45-50	0.0000	0.0057	0.0079
50-55	0.0000	0.0005	0.0000
55-60	0.0000	0.0000	0.0000
60-65	0.0000	0.0000	0.0000
65-70	0.0000	0.0000	0.0000
70-75	0.0000	0.0000	0.0000
75-80	0.0000	0.0000	0.0000

Table 12. Target Velocity Distributions -- Unimproved Roads.

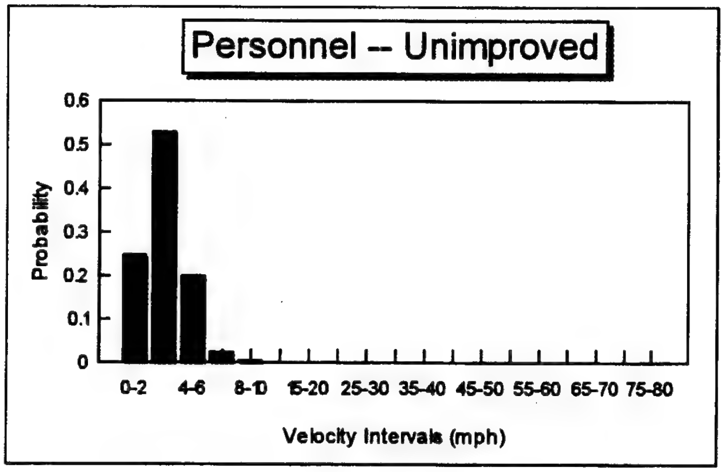


Figure 25. Velocity Distribution: Personnel Target, Unimproved Road.

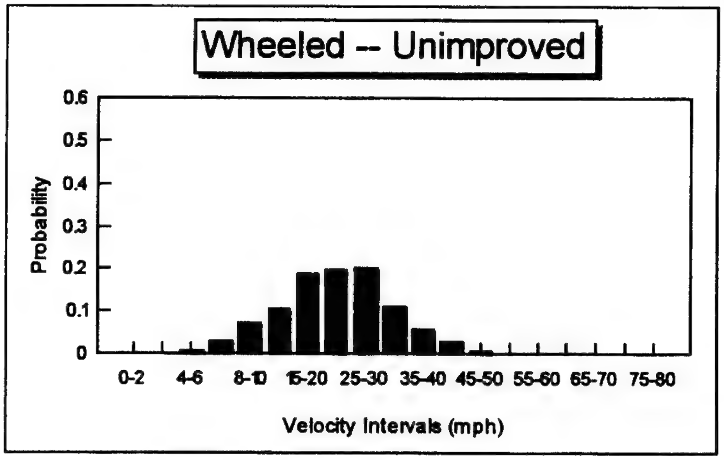


Figure 26. Velocity Distribution: Wheeled Target, Unimproved Road.

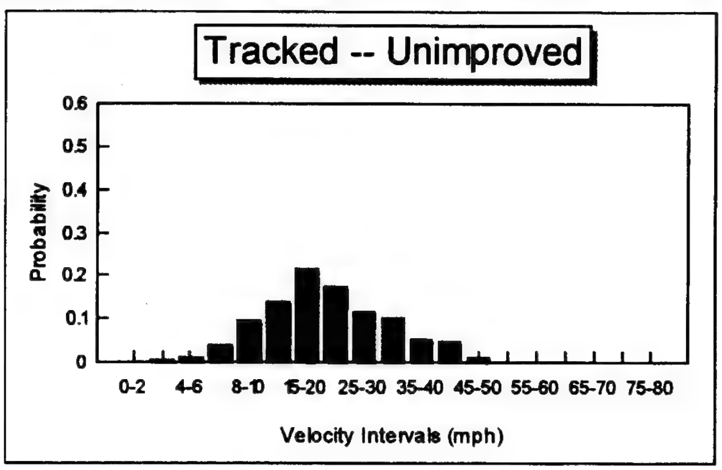


Figure 27. Velocity Distribution: Tracked Target, Unimproved Road.

E. CROSS COUNTRY

This movement condition describes movement through lightly vegetated terrain, under clear, dry, daylight conditions. The terrain was considered to be rolling hills, with no steep ascents or descents. The wheeled column was described as a uniform mixture of heavy and light vehicles. The tracked column was described as a uniform mixture of tanks and armored personnel carriers. The personnel column was described as a column of 200-300 individual, moving in a staggered column. The results are provided in Table 13, and the shapes of the distributions can be seen in Figures 28 through 30. Velocity intervals are given in terms of miles per hour.

Pr(V|TC) -- Cross Country			
Velocity	**Target Class**		
Interval	**Personnel**	**Wheeled**	**Tracked**
0-2	0.3500	0.0024	0.0127
2-4	0.5045	0.0148	0.0280
4-6	0.1297	0.0574	0.0598
6-8	0.0105	0.1316	0.0492
8-10	0.0005	0.1866	0.1180
10-15	0.0000	0.1914	0.1852
15-20	0.0000	0.1522	0.1937
20-25	0.0000	0.1383	0.1862
25-30	0.0000	0.0837	0.0603
30-35	0.0000	0.0368	0.0407
35-40	0.0000	0.0048	0.0370
40-45	0.0000	0.0000	0.0238
45-50	0.0000	0.0000	0.0053
50-55	0.0000	0.0000	0.0000
55-60	0.0000	0.0000	0.0000
60-65	0.0000	0.0000	0.0000
65-70	0.0000	0.0000	0.0000
70-75	0.0000	0.0000	0.0000
75-80	0.0000	0.0000	0.0000

Table 13. Target Velocity Distributions -- Cross Country.

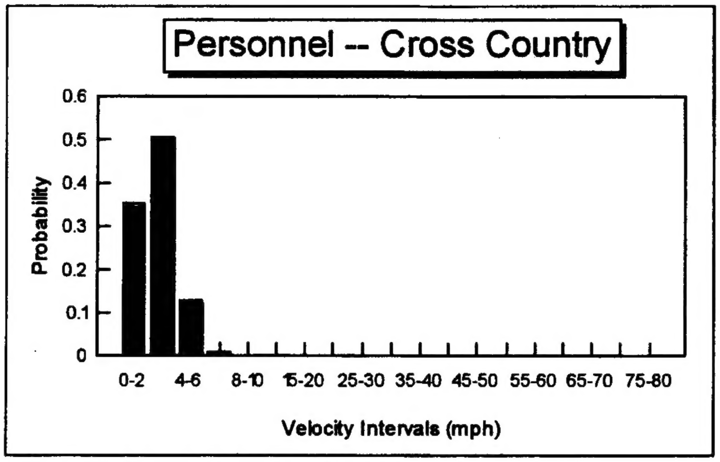


Figure 28. Velocity Distribution: Personnel Target, Cross Country.

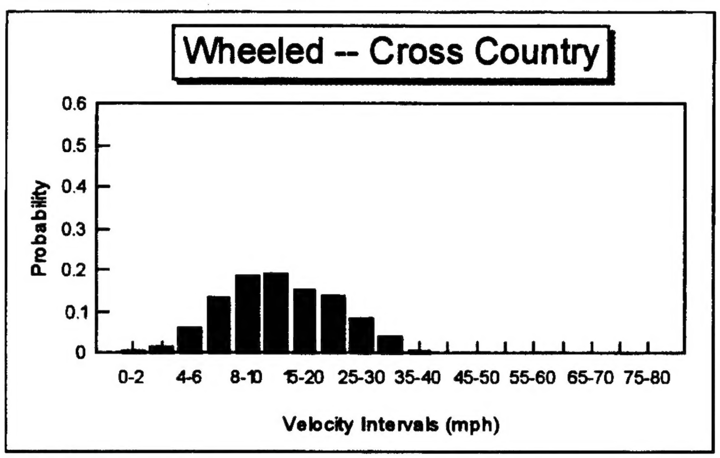


Figure 29. Velocity Distribution: Wheeled Target, Cross Country.

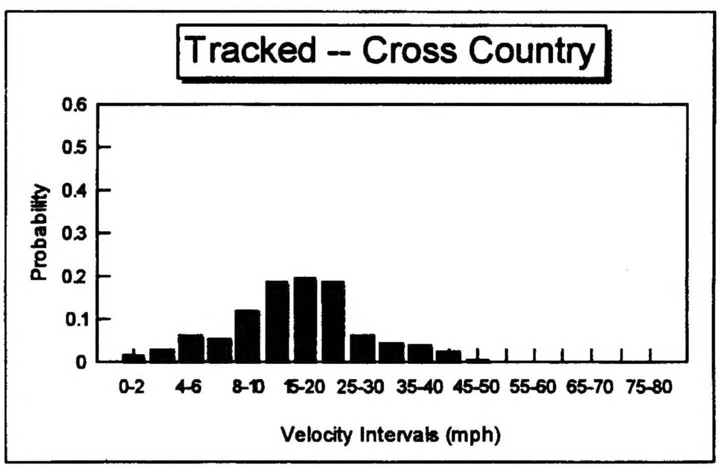


Figure 30. Velocity Distribution: Tracked Target, Cross Country.

F. TRANSFORMING V FOR TARGET CLASSIFICATION

The target classification method in Chapter 4 requires that the velocity distribution be given in terms of observed velocity, $\hat{V}'$, not the true velocity, V. The transformation is made by multiplying the boundaries of the velocity intervals, given in the tables above, by the bias correction factor (Equation 18) specific to the sensors making the velocity observations. An example of such a transformation, using a Tracked target column moving on an Unimproved Road, is provided. In this example, two sensors, on medium setting, placed 300 meters apart, are being used to detect the target, so the bias correction factor is

$$1+\frac{\sigma_1^2+\sigma_2^2}{2d^2}=1+\frac{35^2+35^2}{2(300)^2}$$

$$=1.0136,$$

and the resulting velocity intervals and corresponding probabilities are given below.

Pr(V|TC) – Unimproved Road	
Interval	**Tracked**
0-2.03	0.0005
2.03-4.05	0.0026
4.05-6.08	0.0100
6.08-8.11	0.0383
8.11-10.14	0.0971
10.14-15.20	0.1391
15.20-20.27	0.2178
20.27-25.34	0.1732
25.34-30.41	0.1144
30.41-35.48	0.0997
35.48-40.54	0.0504
40.54-45.61	0.0488
45.68-50.68	0.0079
50.68-55.75	0.0000

Table 14. Transformation Example.

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